USING MULTI-SPECTRAL IMAGERY TO DETECT

AND MAP STRESS INDUCED

BY RUSSIAN WHEAT APHID

By

GEORGES FERDINAND BACKOULOU

Bachelor of Science
Marien Ngouabi University
Brazzaville, Republic of CONGO
1986

Master of Science
Oklahoma State University
Stillwater, OK
1998

Submitted to the Faculty of the
Graduate College of the
Oklahoma State University
in partial fulfillment of
the requirements for
the Degree of
DOCTOR OF PHILOSOPHY
December, 2008

USING MULTI-SPECTRAL IMAGERY TO DETECT

AND MAP STRESS INDUCED

BY RUSSIAN WHEAT APHID

Dissertation Approved:

Dr. Dale Lightfoot

Chair

Dr. C. Norman Elliott

Dissertation Adviser

Dr. G. Terrence Bidwell

Member

Dr. D. Samuel Fuhlendorf

Member

Dr. E. Daniel Storm

Member

Dr. A. Gordon Emslie

Dean of the Graduate College

ACKNOWLEDGMENTS

This work would not be accomplished without the support and help of numerous individuals to whom I am greatly indebted. I would like to express my great gratitude to my dissertation advisor Dr. Norman Elliott for his time, patience, support, guidance and constructive criticism. My great gratitude is also extended to Dr. Dale Lightfoot who accepted to lead this work and also to other committee members, Dr. Terry Bidwell, Dr. Daniel Storm, and Dr. Sam Fuhlendorf for their time, encouragement and contribution. I would like to express my deep appreciation to Mr. Timothy Johnson from the USDA-ARS for his active help, and also to Dr. Vasile Catana and Dr. Phoofolo for their advice.

I owe my family for their support and encouragement lifelong. Great thanks to my mother, my wife Josiane, and daughters Genipha, Christie, and Georgela for their patience, sacrifices, and support. I owe also my church New Covenant Fellowship and my Pastor Dale Barnes, his wife Thresa and the church elders for their support and prayers. Lastly, my thanks are extended to every individual who supported me in successfully completing this work.

TABLE OF CONTENTS

LIST OF TABLES

Table Page

CHAPTER III:

CHAPTER IV:

CHAPTER V:

LIST OF FIGURES

Figure Page

CHAPTER I:

CHAPTER III:

CHAPTER IV:

CHAPTER V:

CHAPTER I

INTRODUCTION

The Russian wheat aphid (RWA) [*Diuraphis noxia* (Mordvilko)] is one of the most important pests that damage small grains around the world (Basky et al., 2003; Clua et al., 2004; Dolatti, et al., 2005; Elliott et al., 2005, Hatting et al., 2004; Reviriego et al, 2004; Stary et al 2003; Royer et al., 2001). The RWA was detected for the first time in the United States near Muleshoe, Texas, in March 1986 (Brewer and Elliott, 2004; Clement et al., 2004; Elliott et al., 2005). Since then, the RWA has spread out in the Great Plains, Rocky Mountains, and Canada (Thomas et al., 2002). The RWA colonizes wheat fields from the stage of emergence to harvest, feeding on young leaves, and causing symptoms that include longitudinal chlorotic streaking and leaf rolling (Figure 1) (Webster et al., 1987). RWA population outbreaks result in widespread loss to the small-grain industry especially in wheat and barley grown in winter and spring (Hein et al, 1998).

The economic losses caused by the RWA total over $1billion to United States agriculture since 1986 (ARS, 2003). Brewer and Elliott (2004) estimate that economic losses in the Great Plains account for 65 percent of losses nationwide. Management of the RWA is an ongoing process. Appropriate tactics to prevent, control and eradicate the pest have not been completed. Farmers are encouraged to scout for the aphids first, and use pesticides after the infestations have reached 30 to 40 percent of tillers infested within a wheat field (Shroyer et al., 2008). Research is still underway to find wheat varieties resistant to RWA and biological control agents to reduce populations of the RWA and mitigate damage. Currently however, chemical insecticides are the main method used to control the pest, but low profits associated with wheat production make insecticide use cost prohibitive and threaten environmental quality (Larsson, 2005; Robinson, 1992). Scouting for aphids is expensive, time consuming, and can lower farmers' profits. A cost effective method to determine both the occurrence of RWA and to differentiate its impact from other stress factors on the wheat crop is needed. Thus, remote sensing technology can be investigated as an alternative tool for scouting wheat fields for aphids, and to detect infestations induced by the RWA.

RWA injury induces stress to a wheat crop by damaging plant foliage, lowering plant greenness, and affecting crop productivity. The lost productivity is a catastrophe for farmers, who usually rely mainly on chemicals to control the RWA infestation. The RWA induces stress to wheat that can be identified by remote sensing technology. It is possible to use remote sensing technology to detect wheat fields that need treatment to control the RWA. Remote sensing offers the possibility to identify RWA infestations within fields comparatively cheaply. However, the question arises, how to spatially identify and distinguish stress induced by RWA from other stress causing factors? Since remote sensing technology can be used to detect crop stress, it may be possible to use this technology to detect and quantify infestation induced by RWA to wheat crops. An investigation is needed to determine the potential of multispectral imagery to identify and assess the intensity of RWA infestation within wheat fields.

The findings of this project progress towards practical methods to detect RWA infested wheat fields using multi-spectral imagery. Ultimately, the goal is to provide growers and managers with an immediately available, non-destructive, inexpensive method for detecting the RWA infestations and the ability to apply site-specific pest control practices when and where needed. Such an approach to pest management could increase growers' profits and improve environmental and human health.

Objective of the study

The overall objective of this study is to determine the capability of multispectral image data to detect infestations induced by the RWA on wheat plants within wheat fields and to develop an approach to distinguish the infestations induced by RWA from other stress causing factors and map them. Specific objectives are to:

1. Determine the relationship between RWA population density and edaphic and/or topographic characteristics within wheat fields;

2. Identify and quantify the spatial pattern of RWA infestation within wheat fields;

3. Develop a method to differentiate the stress induced by RWA from other factors (wheat stress may be a combination of several conditions which vary spatially across the field and may result from topography, nutrient deficiency, drought, diseases, pests, etc).

Assumptions

The assumption in this study is that the population density of RWA is related to environmental conditions within wheat fields such as edaphic and topographic factors. Understanding the relationship between RWA population and environmental conditions may aid in predicting the spatial pattern of RWA infestation within a wheat field. Thus, stress induced by RWA may be differentiable from stress induced by other stressors based not on either reflectance, but on spatial patterns of stressed areas within a field. I seek to differentiate RWA induced stress from that caused by other factors by quantifying the spatial pattern of RWA stress within fields and determining if it can be reliably distinguished from patterns caused by other stress causing factors. Thus, the spatial pattern information was used along with edaphic and topographic information to differentiate RWA infestations.

Hypotheses

The proposed research is centered on the following hypotheses:

a. RWA populations within wheat fields are related to edaphic and /or topographic characteristics;

b. the utilization of airborne multi-spectral imagery collected over RWA infested wheat fields can be used to detect stress induced to wheat plants by the RWA;

c. patches of stress induced by the RWA have a specific shape and a distribution on wheat fields that differs from that of the other stress causing factors.

Organization of the study

The dissertation contains six chapters. Chapter 1 presents the main purpose of the study. Chapter 2 introduces the RWA and reviews current knowledge. The relationship between RWA and topographic and edaphic factors are explored in Chapter 3. In Chapter 4, multi-spectral data are analyzed to generate raster maps for each wheat field. Chapter 5 develops an approach based on landscape metrics, edaphic and topographic variables, combined in a multivariate analysis to differentiate the stress induced by RWA from other stress factors. The chapter 6 concludes the study and provides recommendations for further research.

Figure 1. RWA and strikes on wheat leaves.

References

ARS. 2003. Annual Project Reports. http://www.ars.usda.gov/research/projects/projects.htm?ACCN_NO=407314&showpars=true&fy=2003 visited October 25, 2005.

Basky, Z. 2003. Biotypic and pest status differences between Hungarian and South African population of Russian wheat aphid, Diuraphis noxia (Kurdjumov) Homoptera: Aphidae). Pest Management Science 59(10):1152-1158.

Brewer, M.J., and N.C. Elliott. 2004. Biological control of cereal aphids in North America and mediating effects of host plant and habitat manipulations. Annu. Rev. Entomol. 49:219–242.

Clement, S.L., L. R. Elberson, N. Youssef, F. L. Young, and M. A. Evans. 2004. Cereal aphid and natural enemy populations in cereal production systems in eastern Washington. Journal of Kansas Entomological Society. 77(3):65-173.

Clua, A., A. Vasicek, H. O. Chidichimo, A.F. G. Dixon, A. M. Castro, S. Ramos, and D. O. Gimines. 2004. The biological characteristics and distribution of the greebug , Schizaphis graminum, and Russian wheat aphid, Diuraphis noxia (Hemiptera: Aphididae) in Argentina and Chile. European Journal of Entomology 10(1):193-198.

Dolatti, L., B. Ghareyazie, S. Moharranipour, and M. R. Noori-Daloii. 2005. Evidence for regional diversity and host adaptation in Iranian populations of Russian wheat aphid. Entomologia Experimentalis et Applicata 114(3):171-180.

Elliott, N. C., M. Mirik, Z. Yang, T. Dvirak, M. Rao, J. Michels, V. Catana, M. Phoofolo, K. Giles and T. Royer. 2005. Aircraft multi-spectral remote sensing for Russian wheat aphid infestations. 20th Biennal Workshop on Aerial Photography, Videography and High Resolution Digital Imagery for Resource Assessment. Oct 4-6, 2005. Weslaco, TX.

Hatting, J. L., S. P. Wraight, and R. M. Miller. 2004. Efficacy of beauveria bassiana (Hyphomycetes) for control of Russian wheat aphid (Homoptera:Aphidae) on resistant wheat under field conditions. Biocontrol Science and Technology 14(5):459-473.

Hein, G. L., F. P. Baxendale, J. B. Campbell, A. F. Hagen, J. A. Kalisch. 1998. Russian wheat aphid. File G936 under: INSECTS AND PESTS C-31, Field Crops. Cooperative Extension, Institute of Agriculture and Natural Resources. University of Nebraska, Lincoln, NE.

Larsson H. 2005. A crop loss model and economic thresholds for the grain aphid, Sitobion avenae (F.), in winter wheat in southern Sweden. Crop Protection 24(5):397-405.

Mirik. M. G., J. Michels Jr., S. Kassymzhanova-Mirik, N. C. Elliott, V. Catana, D. B. Jones, R. Bowling. 2006. Using digital image analysis and spectral reflectance data to quantify damage by greenbug (Hemitera: Aphididae) in winter wheat. Computers and Electronics in Agriculture 51:86-98.

Reviriego, M. E., L. R. Descamps, A. A. Ferreroy, and A. A. Suarez. 2004. Field efficacy and laboratory toxicity tests of insecticides against Diuraphis noxia (Homoptera : Aphididae). International Pest Control 46(5):260-262.

Robinson, J. 1992. Russian wheat aphid: a growing problem for small farmers. Outlook on Agriculture 21 (1):57-62.

Royer, T.A., K.L. Giles, S.D Kindler, and N. C. Elliott. 2001. Developmental response of three geographic isolates of Lysiphlebus testaceipes (Hymenoptera: Aphididae) to temperature. Environmental Entomology 30(4):637-641.

Shroyer, J., J. Edwards, Y. Wright, and P. Sloderbeck. 2008. Insect Scouting Guide for Wheat. Small grain solution. High Plains Journal. http://www.hpj.com/smallGrain/scoutingguide/insects.cfm visited August 18, 2008.

Starý, P. Z. Basky, L. K. Tanigoshi, and Z. Tomanovicc. 2003. Distribution and history of Russian wheat aphid, Diuraphis noxia (Kurdj.) in the Carpathian Basin (Hom., Aphididae).

Thomas, J., G. Hein, D. Baltensperger, L. Nelson, and S. Haley. 2002. Managing the Russian Wheat Aphid with resistant varieties. File NF307 under: Insect and Pests. C-5, Field Crops. Nebraska Cooperative Extension. University of Nebraska, Lincoln, NE.

Webster, J.A., K. J. Starks, R. L. Burton. 1987. Plant resistance studies with Diuraphis noxia (Homoptera: Aphididae), a new United States wheat pest. Journal of Economic Entomology.80:944-949.

Yang, Z. 2005. Detection of greenbug infestation on wheat using ground-base radiometry. Doctorate Thesis. Oklahoma State University. Stillwater, OK.

CHAPTER II

REVIEW OF LITERATURE

The purposes of this chapter are to introduce the RWA and review the current knowledge on RWA and others aphids as it relates to the objectives of this study. The review focuses on describing the ecology and biology of the RWA, its management, and the use of remote sensing techniques to detect the impact of damage caused by the aphid.

Russian wheat aphid, biology and damage symptoms

The RWA is a small soft-bodied insect that measures about 2.5 millimeters and is greenish to grayish-green. Karren and Reeve (1989) found four obvious characteristics to identify the RWA. These characteristics are used to differentiate RWA from other aphids that feed on wheat and small grains. The characteristics include extremely short antennae, two tails, absence of prominent cornicles, and a spindle shaped (Hein et al., 1998; Karren and Reeve, 1989; and Peairs, 2004).

RWA feed initially at the base of the leaves near the top of the plant. When their numbers increase and the colony develops, the edges of the leaves begin to roll inward hiding the pest in a tubular shielding structure that makes it less accessible to natural enemies and chemical control (Dollati et al., 2005; Dorry and Assad, 2001; Webster et al., 1987).

The toxins that the RWA injects into plants during the feeding process mainly cause the damage. Phytotoxic substances are injected into the leaves and remove assimilates from leaf vascular tissues (Fouché et al 1984). Plants become purplish and leaves develop longitudinal yellowish and whitish streaks (Hein et al, 1998). A prostrate appearance is noticed on tillers of heavily infested plants.

Temperature seems to play a major role in RWA development. Warmer temperatures favor development and reproduction but shorten the adult life span (Hein et al, 1998). Cooler temperatures slow development and reproduction but lengthen the life span. Temperatures below 40^{o}F nearly stop the development and reproduction of most aphids including the RWA (Hein et al, 1998). A colony of RWA has two types of adult: wingless and winged. The winged adults are often produced when the vigor of the host plant declines (Hein et al 1998).

Aphids reproduce either sexually or asexually (parthenogenesis). In parthenogenic reproduction, all individuals are females that give birth to living young (Hein et al, 1998). RWA colonies produce viviparous winged females under adverse environmental conditions such as when the food source is depleted (Robinson, 1992). RWA have a remarkable ability to reproduce, increasing their population rapidly, which causes a fast progression of crop damage. Aphid reproduction is mediated by temperature. Hein et al (1998) stated that the maximum reproductive potential for the RWA occurs from 15^{o} to 21^{o} C. The adults can live at these temperatures for a month and reproduce at an average of 1.5 young per day. A female adult may produce up to four nymphs daily (Robinson, 1992). The nymph develops and is ready to reproduce in about one and one half weeks at 21^{o}C, and two weeks at 15^{o}C.

Dorschner (1986) concluded that periods of drought promote aphid outbreaks. The outbreaks of aphids occur usually in early or late fall or spring (Brooks, 1989). In fall, the aphids move lower on the plant toward the crown during cold weather. They move upward to feed from new leaves. As the wheat continues to grow, the aphids keep on moving upward to infest new leaves. In spring, they may reach the flag leaf and cause it to roll and trap the emerging head resulting in poor plant pollination (Hein et al., 1998). Heavy infestation by RWA reduces yield and can kill plants. In the stressed condition, plants severely infested by RWA are no longer able to compete with weeds and are more vulnerable to harsh weather and environmental stresses.

Remote sensing and the Russian wheat aphid.

Field scouting for RWA infestations is costly and time consuming. Remote sensing technology may offer an alternative to the traditional ground-based assessment of wheat fields. Remote sensing is defined as the science and art of obtaining information about objects through the analysis of data acquired by a device that is not in contact with the object under investigation (Lillesand and Kiefer, 2000). Yang et al. (2004) stated that it is possible to quantitatively describe an aphid infestation using remotely sensed technology.

Remote sensing may be used to monitor wheat fields for stress induced by insects and other stressors (Mahey et al., 1991; Riley, 1989; Voss, 2004; Zhang et al., 2003), along with other technologies such as geographical information systems (GIS) and global positioning system (GPS). GIS include computer hardware and software with procedures for compiling, storing, retrieving, analyzing, and displaying spatial data. The GPS receiver takes advantage of a set of satellites regulated by the United States Department of Defense to accurately locate a ground position (Strickland et al., 1998).

When using a remote sensing system, four properties of its data should be considered. These properties include spatial resolution, spectral response, spectral resolution and the frequency of the coverage. Spatial resolution refers to the size of the smallest grid cell of the imagery. Spectral response is a degree to which the sensing system collects and responds to the radiation in a spectral band. Spectral resolution is the ability of a sensing system to distinguish between different wavelengths of electromagnetic energy. The frequency of coverage, known as temporal resolution, refers to how often a sensing system is available for data collection at a particular ground site (Lillesand and Kiefer, 2000). The two main platforms in remote sensing are airborne based and satellite-based. Airborne-based systems provide image data that have higher spatial and spectral resolution than satellite-based systems. They can be used in areas when the conditions are optimal. In contrast, satellite–based platforms are in fixed orbits and data acquisition interval and spatial resolution are fixed and depend on the characteristics of the particular system. The cost of data varies according to image type, size and level of preprocessing.

Remote sensing technology can improve crop management decision making, and help growers control pests before they influence the overall crop yield (Butterfield and Malmstrom, 2006; Waheed et al., 2006).

Plants subjected to abiotic and biotic constraints may be under stress. Stress is defined as disturbance that adversely influences plant growth (Jackson, 1986). Stress affects plant morphology and physiological change such as the decrease in photosynthesis is associated with changes in spectral reflectance patterns (Mitternicht, 2004). Indeed, stress can affect plant productivity and the objective is to detect it as early as possible to minimize its effect on yield production.

Remote sensing techniques have been used to detect stresses caused by water deficits, insects, nutrient deficiencies, salinity, and diseases (Jackson, 1986). Maracchi et al. (1988) investigated the water stress effects on reflectance and emittance of winter wheat in a field experiment in Central Italy. Their objective was to use remote sensing techniques to detect the onset and the degree of plant water stress in crops growing in fields that have undulating terrain. Ground-based measurements of canopy reflectance and emittance in five Thematic Mapper wavebands were obtained using nadir and off-nadir viewing angles. The study measured the surface canopy temperature, which they used to calculate the Crop Water Stress Index. This canopy temperature-based stress index showed sensitivity to the beginning of plant stress and was correlated with the physiological measurement of water status.

Remote sensing can also be used to estimate nutrient deficiency and help make decisions about crop management. Wright (2004) used remote sensing at the canopy level to estimate wheat nitrogen content for grain protein management. They collected and compared data from aerial and satellite platforms, and a ground based spectrometer. Spectral vegetation indices such as normalized differenced vegetation index (NDVI), Green NDVI, difference vegetation index (DVI), and RVI were derived from all instruments and compared with initial nitrogen treatments, plant tissue analyses, grain yield and protein.

Zhao et al. (2004) detected nitrogen availability for wheat canopy. They computerized spectral indices such as simple ratio, normalized difference vegetation index (NDVI) and photochemical reflectance index from wavelength of maximum or minimum reflection related to leaf area index, leaf chlorophyll concentrations, and dry phytomass of wheat plant subjected to six levels of fertilization of nitrogen. They found that the maximum reflectance occurred in the green band near 554 nm and the minimum reflectance was in the red band near 670 nm. Their investigation concluded that the redefined PRI (PRI-re), expressed as (R551 – (570 –g) – Rg) / (R531- (570-g) + Rg), based on 554 nm was the most sensitive indicator of N availability for the wheat canopy. Thus, remote sensing data offers the possibility to identify the heterogeneity in plant stress within fields.

Digital imaging with narrow wavebands can detect plant stress early. Carter and Miller (1994) investigated an early detection of plant stress using digital images of soybean canopies obtained in 6 to 10 nm bandwidths. They concluded that reflectance in narrow wavebands within the 690 – 700 nm region and their ratio with near-infrared reflectance provided earlier detection of stress-induced chlorosis compared with broad band systems or narrow bands located at lesser wavelengths.

Yang, (2005) demonstrated that it is feasible to use ground-based radiometry to identify differences in reflectance in red and near infrared (NIR) bands that relate to the intensity of greenbug infestation on wheat. The band centered at 694 nm and the vegetation indices derived from bands centered at 800 and 694 nm (near infrared and visible) were the most sensitive to stress induced by greenbug infestation.

Few studies have focused on spatial patterns of wheat stress induced by aphids using remote sensing technologies. Most of the studies on spatial pattern analysis focus on field visual counts of aphids and use geostatistical analysis (Elliott and Kieckheffer, 1987; Feng and Nowerski, 1992; Longley et al., 1997; Winder et al., 1999, Winder et al., 2005). Johnson et al., (2003) used aerial photography for spatial pattern analysis of late blight infection in irrigated potato circles. Aerial photos were taken 6 times at 6 to 21 day intervals. Photographs were scanned and pixels representing approximately one square meter in the field were used for the analysis. The study concluded that the technique was effective to quantitatively assess the disease patterns in large fields, and it was also useful in quantifying the intensification of the aggregation during the epidemic development. Voss (2004) used remote sensing and landscape metrics to identify and assess site-specific damage in cultivation systems of Central Europe. She used QuickBird-2 satellite multispectral images with spatial resolution of 2.8 meters and a panchromatic image with 0.7-meter spatial resolution. The spatial resolution of both images was modified to produce a suitable data set. Images were classified to identify the plant damage in different data sets. Then landscape metrics were computed to evaluate the influence of spatial resolution on the identification of site-specific plant damage. According to this study, there is a resolution threshold beyond which spatial pattern is difficult to perceive.

Reflectance measured by a sensor is a combination of the reflected radiances from the various surfaces. The spectral signature of the pixel is a combination (linear or non-linear) of the spectral signatures of the component surfaces. Spectral mixture analysis is a method that can help determine spectrally distinct components that contribute to the spectral signal of mixed pixels (Goodwin et al., 2005; Garcia-Haro et al., 2005). The method has been used to assess pine plantation canopy condition subjected to a range of damaging agents. Goodwin et al., (2005) explore the endmembers that could be identified within 4-channel spectral imagery and assess the ability to unmix imagery using the identified endmembers. Endmembers are spectral features recognizable in an image (Goodwin et al., 2005) and are defined as a pure surface cover such as vegetation, soil, sunlit, shadow etc.   Garcia-Haro et al., (2005) stated that spectral mixture analysis is adequate for dealing with scenes in which the spatial variability within a pixel is high. It provides a means to detect and represent components at the subpixel level. Souza et al., (2005) used spectral mixture analysis and combined spectral and spatial information to map canopy damage from selective logging and forest fires. The technique may be useful in this study to differentiate stress induced by RWA from other stressors.

Aphid density and edaphic and topographic characteristics

Few studies have addressed the relationship between RWA population density and soil characteristics. In this review, soil characteristics refer to soil texture, such as clay, sand, and loam and topographic characteristics that include slope and aspect. Winder et al. (1994) have reported a very high proportion of cereal aphids that fall to the ground each day, during spring. Plants growing in enriched soil may be more attractive to aphids as hosts because they contain higher nutrient concentration. Wurst and Hefin (2003) stated that the presence of earthworms increase populations of aphids in a particular soil environment. Wurst and Hefin (2003) found a higher number of parasitized aphids (mummies) in enriched soils compared to low nutrient soils.

Aphid and virus incidences can be related to a range of crop and field characteristics, in particular geographic position, topography and climate, extent of arable land, and the aspect and size of the field. Foster et al. (2004) surveyed the occurrence of barley yellow dwarf virus and its aphid vectors in relation to field characteristics. They analyzed the incidence of the virus and its aphid vector in untreated parts of wheat and barley fields in 1995-1998 in the United Kingdom. They found that the incidence of virus in spring was related to the incidence of aphids in the preceding autumn. Foster et al. (2004) analyzed the occurrence of the number of aphids in 4 soil classes: sandy, loam, clay loam, and clay. They found that aphid number was different across the four classes of soil texture. The aphid *Rhopalosiphum padi* was more abundant on loamy soils and least abundant on clay, while *Sitobon avenae* was more abundant on sandy and least on clay loam. As for the aspect, Foster et al. (2004) found higher density of *R. padi* on fields facing southwest.

Plant cover and species community vary across slopes (Nevo et al., 1999). In the northern hemisphere, south-facing slopes are exposed to more solar radiation than north-facing slopes (Auslander et al., 2003). South facing slopes are warmer, drier and have more a more variable microclimate than the north facing slopes. Auslander et al. (2003) found higher densities of the aphid *Aploneura lentisci* in south facing slope.

Hammon and Peairs (1992) sampled RWA to document the distribution and density within fields of small grains in western Colorado. RWA were found throughout fields with east-west furrows, but plants located on the south-facing slope of the irrigation beds had the highest infestations. RWA were found only on plants with south facing slopes of irrigation ditches at either end of the field in fields with north facing slopes.

There was a higher density of RWA on the south facing slopes of beds than at other sample sites in fields with east-west furrows. In fields with north-south furrows, RWA were evenly distributed over beds. Infestations increased on the south slopes and middle of beds in fields with east-west furrows during winter, but remained unchanged in fields with north-south furrows. Temperatures played a major role, as it was higher on the south slope of the bed.

References

Auslander, M., E. Nevo, and M. Inbar. 2003. The effects of slope orientation on plant growth, developmental instability and susceptibility to herbivores. Journal of Arid Environments 55(3):405-416.

Butterfield, H.S., and C. M. Malmstrom. 2006. Experimental use of remote sensing by private range managers and its influence on management decisions. Rangeland Ecology and Management 59(5):541-548.

Brooks, H. L. 1989. The greenbug: A pest in wheat. Entomology 163. Kansas State University Agricultural Experiment Station and Cooperative Extension Service. MF-925. http://www.oznet.ksu.edu/library/entml2/MF925.PDF visited October 04, 2006

Carter, G. A., and R. L. Miller. 1994. Early detection of plant stress by digital imaging with narrow stress-sensitive wavebands. Remote Sensing of Environment 50:295-302.

Ciesla, W.M., D. D. Bennett, and J. A. Caylor. 1984. Mapping effectiveness of insecticide treatments against pandora moth with color-IR photos (ponderosa pine, Arizona, USA). Photogrammetric Engineering & Remote Sensing 50(1): 73-79.

Dolatti, L., B. Ghareyazie, S. Moharranipour, and M. R. Noori-Daloii. 2005. Evidence for regional diversity and host adaptation in Iranian populations of Russian wheat aphid. Entomologia Experimentalis et Applicata 114(3):171-180.

Dorry, H.R., and M. T. Assad. 2001. Inheritance of leaf shape and its association with chlorosis in wheat infested by Russian wheat aphid (*Diuraphis noxia*).Journal of Agricultural Science 137(2):169-172.

Dorschner, K. W. 1986. Studies of insect-plant interactions: greenbugs (Homoptera: Aphidae), host-plant resistance, and drought stress in winter wheat. Doctorate Thesis. Oklahoma State University. Stillwater, OK.

Elliott, N. C., and R. W. Kieckheffer. 1987. Spatial Distribution of cereal aphid [Homoptera: Aphididae] in winter wheat and spring oats in South Dakota. Environmental Entomology 16:896-901.

Elliott, N. C., M. Mirik, Z. Yang, T. Dvirak, M. Rao, J. Michels, V. Catana, M. Phoofolo, K. Giles and T. Royer. 2005. Aircraft multi-spectral remote sensing for Russian wheat aphid infestations. 20th Biennal Workshop on Aerial Photography, Videography and High Resolution Digital Imagery for Resource Assessment. Oct 4-6, 2005. Weslaco, TX.

Feng, M. G., and R. M. Nowerski. 1992. Spatial patterns and sampling plans for cereal aphids (Hom.: Aphididae) killed by entomophthoralean fungi and hymenopterous parasitoids in spring wheat. Entomophaga 37(2):265-275.

Foster, G.N., R. Harrington, S. Blake, S. J. Tones., and I. Barker. 2004. Occurrence of barley yellow dwarf virus in autumn-sown cereal crops in the United Kingdom in relation to field characteristics. Pest Management Science 60(2):113-125.

Fouché, A., RL. Verhoeven, P. H. Hewitt, M. C. Walters, C. F. Kriel, and J. DeJager. 1984. Russian aphid (Diuraphis noxia) feeding damage on wheat, related cereals and a Bromus grass species. In M.C. Walters (ed.) Progress in Russian wheat aphid (Diuraphis noxia Mordw.) research in the Republic of South Africa. Technical Communication No 191. Department of Agriculture, Johannesburg . Republic of South Africa 191:22-23.

Garcia-Haro, F. J., S. Sommer, and T. Kemper. 2005. A new tool for variable multiple endmember spectral mixture analysis (VMESMA). International Journal of Remote Sensing 26(10):2135-2162.

Goodwin, N., N. C. Coops, and C. Stone. 2005. Assessing plantation canopy condition from airborne imagery using spectral analysis and fractional abundances. International Journal of Applied Earth Observation and Geoinformation 7:11-28.

Hammon, R.W.,and F. B. Peairs. 1992. Distribution of overwintering Russian Wheat Aphid (Homoptera: Aphididae) in furrow irrigated small grains in western Colorado. Journal of Econ. Entomol. 85:2452-2458.

Hein, G. L., F. P. Baxendale, J. B. Campbell, A. F. Hagen, J. A. Kalisch. 1998. Russian wheat aphid. File G936 under: INSECTS AND PESTS C-31, Field Crops. Cooperative Extension, Institute of Agriculture and Natural Resources. University of Nebraska, Lincoln, NE.

Jackson, R. D. 1986. Remote sensing of biotic and abiotic plant stress. Annual Reviews of Phytopathology 24:265-287.

Johnson, D. A., J. R. Alldredge, P. B. Hamm, and B. E. Frazier. 2003. Aerial photography used for spatial pattern analysis of late blight infection in irrigated potato circles. Phytopathology 93(7):805-812.

Karren, J. B., and T. A. Reeve. 1989. Russian wheat aphid in Utah. Fact Sheet no 67. Extension Entomology. Utah State University. Logan, UT

Larsson H. 2005. A crop loss model and economic thresholds for the grain aphid, Sitobion avenae (F.), in winter wheat in southern Sweden. Crop Protection 24(5):397-405.

Lillesand, T.M., and R.W. Kiefer. 2000. Remote Sensing and Image Interpretation. 4th Edition. John Willey and Sons New York, NY.

Longley, M., P. C. Jepson, J. Izquierdo, and Sotherton. 1997. Temporal and spatial changes in aphid and parasitoid population following applications of deltamethrin in winter wheat. Entomologia Experimentalos et Applicata 83(1):41-52.

Mahey, R. K., R. Singh, S. S. Sidhu, and R. S. Narang. 1991. The use of remote sensing to assess the effects of water stress on wheat. Experimental Agriculture 27(4): 423-430.

Maracchi, G., G. Zipoli, P.J. Pinter Jr, and R. J. Reginato. 1988. Water stress effects on reflectance and emittance of winter wheat. In Proceedings of the 8th EARSeL Symposium : Alpine and Mediterranean areas : a challenge for remote sensing : Capri (Naples), Italy.

Mirik., M. G., J. Michels Jr., S. Kassymzhanova-Mirik, N. C. Elliott, V. Catana, D. B. Jones, R. Bowling. 2006. Using digital image analysis and spectral reflectance data to quantify damage by greenbug (Hemitera: Aphididae) in winter wheat. Computers and Electronics in Agriculture 51:86-98.

Mitternicht, G. 2004. Vegetation indices derived from high-resolution airborne videography for precision crop management. International Journal of Remote Sensing 24(14):2855-2877.

Nevo, E., Fragman, O., Dafni, A., and Beiles, A. 1999. Biodiversity and interslope divergence of vascular plants caused by microclimatic differences at "Evolution Canyon", Lower Nahal Oren, Mount Carmel, Israel. Isr. J. Pl. Sci. 47: 49–59.

Peairs, F. B. 2004. Aphids in small grains. Cooperative Extension – Horticulture. Colorado State University. No 5.568.

Riley, J. R. 1989. Remote Sensing in entomology. Annual Review of Entomology 34:247-271.

Robinson, J. 1992. Russian wheat aphid: a growing problem for small farmers. Outlook on Agriculture 21 (1):57-62.

Souza, Jr. C.M., D. A. Roberts, and M. A. Cochrane. 2005. Combining spectral and spatial information to map canopy damage from selective logging and forest fires. Remote Sensing of Environment 98(2-3):329-343.

Strickland, R. M., D.R. Ess, and S. D. Parsons. 1998. Precision farming and precision pest management: the poser if new crop production technologies. Journal of Nematology 30(4):431-435.

Voss, K. 2004. Remote sensing and landscape metrics to identify and to assess site-specific damage in cultivation systems of Central Europe. Erkunde 58(4):283-289.

Waheed, T., E.Paulet, R. B. Bonnell, and S. O. Prasher. 2006. Measuring performance in precision agriculture: CART-A decision tree approach. Agricultural Water Management 84(1-2):173-185.

Webster, J.A., K. J. Starks, R. L. Burton. 1987. Plant resistance studies with Diuraphis noxia (Homoptera: Aphididae), a new United States wheat pest. J. Econ. Entomol.80:944-949.

Winder, L., P. I. Sopp, D. J. Hirst, N. Carter, and S. D. Wratten. 1994. Estimating predation of the grain aphid Sitobion avenae by polyphagous predators. Journal of Applied Ecology 31(1):1-12.

Winder, L., J. N. Perry and J. M. Holland. 1999. The spatial and temporal distribution of the grain aphid Sitobion avenae in winter wheat. Entomologia Experimetalis et Applicata 93(3):277-290.

Winder, L., J. N. Perry, C. Wooley, C. J. Alexander, J. M. Holland, and W. O. C. Symondson. 2005. Predatory activity and spatial pattern: The response of generalist carabids to their aphid prey. Journal of Animal Ecology 74(3):443-454.

Wratten, S. D., A. D. Watt, N. Carter, and J. C. Entwhistle. 1990. Economic consequences of pesticide use for grain aphid control on winter wheat in 1984 in England. Crop Protection 9:73-78.

Wright, D. 2004. Canopy reflectance estimation of wheat nitrogen content for grain protein management. GIScience and Remote Sensing. 41(4):287-300.

Wurst, S., and J. T. Hefin. 2003. Indirect effects of earthworms (Aporrectodea caliginosa) on an above-ground tritrophic interaction. Pedobiologia 47(1):91-97.

Yang, Z., M. N. Rao, D. Kindler, and N. C. Elliott. 2004a. Remote sensing to detect plant stress, with particular reference to stress caused by the greenbug: A review. Southwestern Entomologist 29(3):227-236.

Yang, Z., M. N. Rao, N. C. Elliott, S.D. Kindler, T. W. Popham. 2004b. Using ground-based multispectral radiometry to detect stress in wheat caused by greenbug (Homoptera:Aphididae) infestation. Computers and Electronics in Agriculture 47:121-135.

Yang, Z. 2005. Detection of greenbug infestation on wheat using ground-base radiometry. Doctorate Thesis. Oklahoma State University. Stillwater, OK.

Zhang, M., Z., X. Liu, S. L.Ustin. 2003. Detection of stress in tomatoes induced by late blight disease in California, USA, using hyperspectral remote sensing. International Journal of Applied Earth Observation and Geoinformation 4(4):295-310.

Zhao, C., Q. Zhou, J. Wang, and W. Huang. 2004. Spectral indices redefined in detecting nitrogen availability for wheat canopy. Communications in Soil Sciences and Plant Analysis 35 (5 & 6):853-864.

CHAPTER III

RELATIONSHIP BETWEEN RWA POPULATION DENSITY AND EDAPHIC AND/OR TOPOGRAPHIC CHARACTERISTICS WITHIN WHEAT FIELDS

Abstract

The Russian wheat aphid (RWA), *Diuraphis noxia* (Mordvilko) was first detected in the United States in the 1980's. Since then, the RWA has spread rapidly, from Texas to the Rocky Mountains and into Canada causing an economic loss estimated at over one billion dollars to the United States agriculture. This study explores the spatial relationship between RWA population density and edaphic or topographic factors within wheat fields. Multiple regression analysis was applied on data collected from six wheat fields with fixed sample points, located in four States, Texas, Colorado, Wyoming, and Nebraska. Data consisted of RWA population density, topographic factors such as Aspect, Elevation, and Slope and edaphic factors such as the percentage of clay, silt, and sand. The study demonstrated that there is a relationship between RWA population density and topographic and edaphic factors. Slope and percent sand showed statistical significantly relationships with RWA density in four regression models explored. Slope and percent sand explained the variation of 32.5 percent of RWA population density within wheat fields.

Introduction

The Russian wheat aphid (RWA), *Diuraphis noxia* (Mordvilko) (Hemiptera:Aphididae) is native to the Black Sea region of Euroasia where it occasionally causes losses to the wheat crop (Grossheim, 1914). It was first described in the early 1900s when outbreaks occurred in Moldova and Ukraine (Halbert and Stoetzel, 1998). RWA is now one of the most significant pests of winter wheat *Triticum aesticum* and barley, *Hordeum vulgare* (Puterka et al., 2007). RWA is currently in most regions that produce wheat, except Australia (Botha and Hardie, 2000; Hughes and Maywald, 1990) and northeastern China (Robinson, 1992). RWA was detected for the first time in Ethiopia in 1973 (Adisu and Freier, 2003), in South Africa in 1978 (Walters, 1984), in central Mexico in 1980 (Gilchrist et al., 1984), in the United States (US) in 1986 (Stoetzel, 1987), in Canada in 1988 (Jones et al., 1989) and Argentina in 1991 (Reviriego et al., 2004). Starý (1999) reported that the RWA was first detected in central Europe in 1989.

Since its detection in the US, the RWA spread rapidly, from Texas to the Rocky Mountains and into Canada (Thomas et al., 2002). The economic loss caused by the RWA is estimated at over one billion dollars in the United States (Webster et al., 2000). Several studies were undertaken to eradicate or control the RWA, to find crop varieties resistant, and other management approaches (Bosque-Perez et al., 2002; Dorry and Assad, 2001; Reviriego et al., 2004; Robinson, 1992).

RWA causes stress to a wheat crop (Hein et al, 1998). The aphid feeds on plant phloem which causes serious damage to wheat plants (Saheed et al., 2007). Riedell

(1989) and Walters et al., (1980) noticed that the visible effects that result from RWA damage include white, yellow, purple and reddish longitudinal streaks, and leaf rolling.

RWA infest wheat most years and may lead occasionally to significant yield reduction when biotic and abiotic conditions are optimal for rapid population growth. There must exist biotic and abiotic conditions that favor the development of RWA populations and trigger the outbreaks. Several studies have investigated the relationship between insects and environmental conditions. Mattson and Haack, (1987) stated that outbreaks of phytophagous insects were caused by drought. Orwig et al. (2002) studied environmental factors associated with the decline of the eastern hemlock (*Tsuga Canadensis*) infested by the hemlock woolly adelgid (HWA) (*Adelges stugae*), a small aphid like insect native to Japan that was threatening eastern North American forests. Orwig et al. (2002) found that variation of the pest population was related to landscape characteristics. In their study, HWA was abundant on xeric aspects, while slope and elevation exerted less influence over tree mortality. Temperature and rainfall were identified as environmental factors that were associated with aphid abundance in north-west Europe (Cocu et al., 2005).

The present study was the first of a series of three studies conducted to assess RWA infestation within wheat fields. The goal of this study was to explore the spatial relationship between the RWA population density and edaphic or topographic conditions within wheat fields. This information is useful for determining where in a field RWA will be most numerous and consequently damage is most likely to occur. Farmers in this context will be able to get complete spatial information about features in their fields to assist management decisions. The relationship between RWA population density and edaphic and topographic variables may help differentiate RWA induced stress from other factors if the RWA has associations with these variables that differ from those of other stress causing factors.

Materials and Methods

Data collection

The study area included wheat fields located in Colorado, Nebraska, Texas, and Wyoming that were monitored as part of an Areawide Pest Management (AWPM) for wheat project, where fixed sampling plots were set to collect data for the project (Table 1). Data collected for each field were layers of spatial information that included RWA population, aspect, elevation, slope, clay, silt and sand (Fig.1).

Initially, 13 fields were selected in four States: Texas, Colorado, Wyoming, and Nebraska. Out of these 13 selected fields, 6 were retained for the present study. The soil texture was the criteria for the field selection. Wheat fields that had only one soil texture were eliminated from the study.

Data were created in a geographic information system (GIS) environment and transferred to a spreadsheet for statistical analysis. RWA population data were collected from field demonstration sites compiled from the AWPM program housed at the USDA-ARS Plant Science Research Laboratory on a server devoted to the project. Soil type information were collected from Soil Survey Geographic data (SSURGO) from the Natural Resources Conservation Service (NRCS), and aspect, elevation, and slope information were derived from Digital Elevation Model (DEM) data from the United States Geological Survey.

RWA Data

The RWA population data were obtained from the AWPM database. The AWPM database was archived at the USDA-ARS Plant Science Research Laboratory, Stillwater, OK. This database consisted of data on the RWA and greenbug from demonstration fields of the AWPM project. The RWA population data were collected each month from March to June or July from 2003 to 2006. The RWA population data reported in this study are average counts for May and June, or June and July for fields located in Wyoming and Nebraska. The AWPM data were collected from a 5 by 5 grid of uniform sized cells that covered the entire wheat field and resulted in a total of 25 sampling points in each wheat field. Each sampling point was georeferenced using a Global Positioning System (GPS) unit.

Several types of data were collected at each point. In this study I was interested in RWA population data. The RWA population data were collected using the Berlese funnel technique for which sampling, that included the soil at the base of the wheat plants, were collected with a spade with a 15 centimeter wide blade. Samples were collected and placed in bags. Then they were processed in a Berlese funnel in the laboratory as soon as possible after collection. The number of RWA per sample was recorded along with the coordinates of sampling point. RWA population data were transformed to logarithms for the purpose of data analysis using the following formula:

$$Y = \text{Ln}(\text{RWA population} + 1).$$

Topographic data

Aspect, elevation, and slope were topographic variables measured for each sample point in each field. Topographic data were derived from USGS 10-meter Digital Elevation Model (DEM) data. DEM data were downloaded from the USGS website for each study field. DEM data for each field were used to develop layer maps of Elevation, Slope and Aspect, using the Surface procedure in ArcView software (version 3.3) from ESRI.

Elevation in this study was a relative elevation that measured the elevational variation from the mean elevation for each field. Aspect was derived from the DEM data. It is an angular measure in degrees from 0 to 360, as presented in Table 1. Aspect represents the direction of the slope face for a sample point relative to North. Slope can be measured in degrees or in percent slope. In this study we used percent slope, which is the percentage change in the surface value over distance. Slope was also derived from the USGS 10-meter DEM data using the Surface procedure in ArcView.

Soil data

Soil data were acquired from the Soil Survey Geographic database (SSURGO) housed by the Natural Resources Conservation Service (NRCS). The SURGO database contains physical and chemical soil properties for several soil series identified in the US. I downloaded soil shape files and soil names to build the soil layer for each selected wheat field. Soils information was first grouped by soil name, then by texture according to the soil triangle for each soil texture. Soil texture was characterized by the percentage of Clay, Silt and Sand each soil contained (see Table 2).

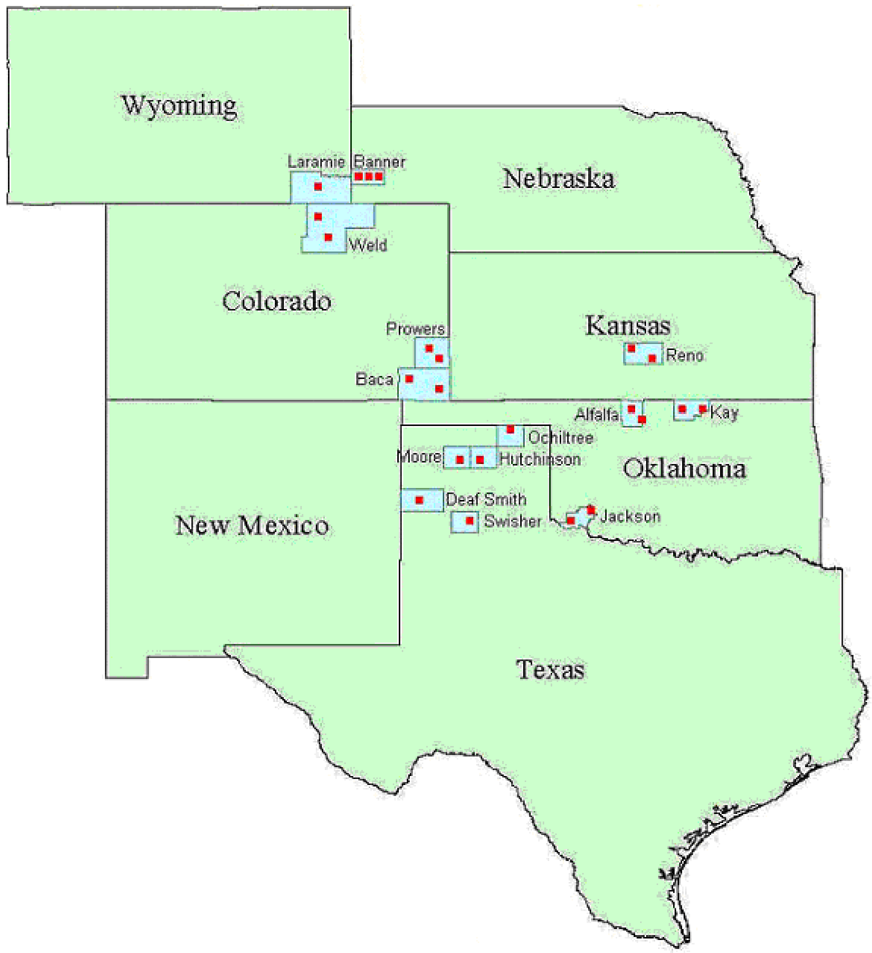

Figure 1. Field demonstrations for the Areawide Management Project by State and County. The square points mark the location of each field.

Table 1. Value of Aspect variable, direction of slope based on 360 degrees. The table describes eight cardinal directions with flat as a slope of zero. North is [0-22.5] and [337.5-360] degrees, East is [67.5-112.5] degrees

Aspect	*Value*
Flat	-1
North	0 - 22.5
Northeast	22.5 - 67.5
East	67.5 - 112.5
Southeast	112.5 - 157.5
South	157.5 - 202.5
Southwest	202.5 - 247.5
West	247.5 - 292.5
Northwest	292.5 - 337.5
North	337.5 – 360

Table 2. Dominant soils in the study area and their slopes and textures. The table contains information retrieved from SSURGO database. Percentage of Clay, Silt and Sand was estimated using the soil texture triangle

Map Symbol	*Soil Name*	*Texture*	*Clay (%)*	*Silt (%)*	*Sand (%)*
Bc	Kim Loam 3 to 5 %	Loam	20	40	40
Da	Dalhart Fine Sandy Loam 0 to 1%	Sandy Loam	18	22	60
Db	Dalhart Fine Sandy Loam 1 to 3%	Sandy Loam	18	22	60
Dc	Dalhart Fine Sandy Loam 0 to 3%	Sandy Loam	18	22	60
Dd	Dalhart Loamy Fine Sand 0 to 3%	Loamy Sand	8	10	82
De	Dalhart Loamy Fine Sand 0 to %	Loamy Sand	8	10	82
La	Corlena Loamy Fine Sand o to 1%	Loamy Sand	8	10	82
Ma	Conlen Fine Sandy Loam 3 to 5%	Sandy Loam	18	22	60
Mb	Conlen Loam 1 to 3%	Loam	20	40	40
Mc	Conlen Loam 3 to 5%	Loam	20	40	40
Md	Conlen-Dalhart Complex 1 to 3%	Complex	30	60	10
Me	Conlen-Plack Complex 3 to 12%	Complex	30	60	10
Pa	Sunray Clay Loam 0 to 3%	Clay Loam	35	30	35
Pb	Sunray Clay Loam 1 to 3 %	Clay Loam	35	30	35
Pc	Plack-Kerrick Complex1 to 3%	Complex	30	60	10
Ra	Ness Clay Loam 0 to 1%	Clay Loam	35	30	35
Rb	Sherm Clay Loam 0 to 1%	Clay Loam	35	30	35
Rc	Sherm Clay Loam 0 to 1 to 3%	Clay Loam	35	30	35
Rd	Rickmore Fine Sandy Loam 0 to 1%	Sandy Loam	18	22	60
Re	Gruver Loam 0 to 1%	Loam	20	40	40
Rf	Travessilla-Rock Outcrop Complex 10 to 50%	Complex	30	60	10
Sa	Manzano Clay Loam 0 to 1%	Clay Loam	35	30	35
Ta	Travessilla Stony Loam 3 to 12 %	Loam	20	40	40
Vb	Vona-Valent Complex 3 to 5 %	Complex	30	60	10

Data analysis methods

I used ArcView to create the data layers described above. These layers included RWA population density, Relative Elevation, Aspect, Slope, and the percent of Clay, Silt and Sand for each selected wheat field. Layers were intersected to generate a unique layer for each field. Attributes of each layer were exported to an Excel table, then to SPSS version 16 (SPSS Inc., 2007) for statistical analysis. SPSS version 16 was used to correlate the population density of RWA with the topographic and edaphic variables. The correlation matrix helped in selecting variables that were further analyzed in a multivariate regression analysis (Figure 2). The level of statistical significance used in the analysis was 0.05.

After examining and evaluating the relationship between variables from the correlation matrix, variables with strong relationships with RWA density were selected for multiple regression modeling. SPSS was then used for the regression analysis. Four multiple regression models were explored for the relationship between RWA population density and the topographic and edaphic variables. I fitted two multiple linear regressions, and two quadratic regressions using stepwise procedure for the search for variables to include in the model. The forward stepwise regression procedure allowed me to select or eliminate variables one at the time to avoid including variables with either no predictive ability or variables that were highly correlated with other predictor variables. The stepwise procedure was that each variable that was added in the model could be eliminated if the variable contribution to the model was not statistically significant.

The stepwise regression worked by successively adding or removing variables based on the F-statistic of each estimated coefficient. The forward stepwise regression I used in this study began with no variables in the model, and the automation proceeded to add one variable at a time. For each variable that was not yet entered in the model an F-statistic was also computed and reported as F-to-enter. Then, SPSS automatically entered the variable with the highest F-to-enter or removed the variable with the lowest F-to-remove on the basis of criteria I defined in the linear regression options. In this study the default criteria for the stepwise regression option were an F of 3.00 for entry or 2.71 for removal (Warner, 2008; and Grimm and Yarnold, 1995).

The form of the relationship between RWA population density and explanatory variables was algebraically represented as:

$Y = a + b_1X_1 + b_2X_2 + ... + b_nX_n$

where Y is the Log of RWA population density, plus 1 [Ln(RWA +1)],

$X_1 .... X_n$ are independent variables representing topographic and edaphic variables measured for each field, and

$b_1 ... b_n$ are regression coefficients.

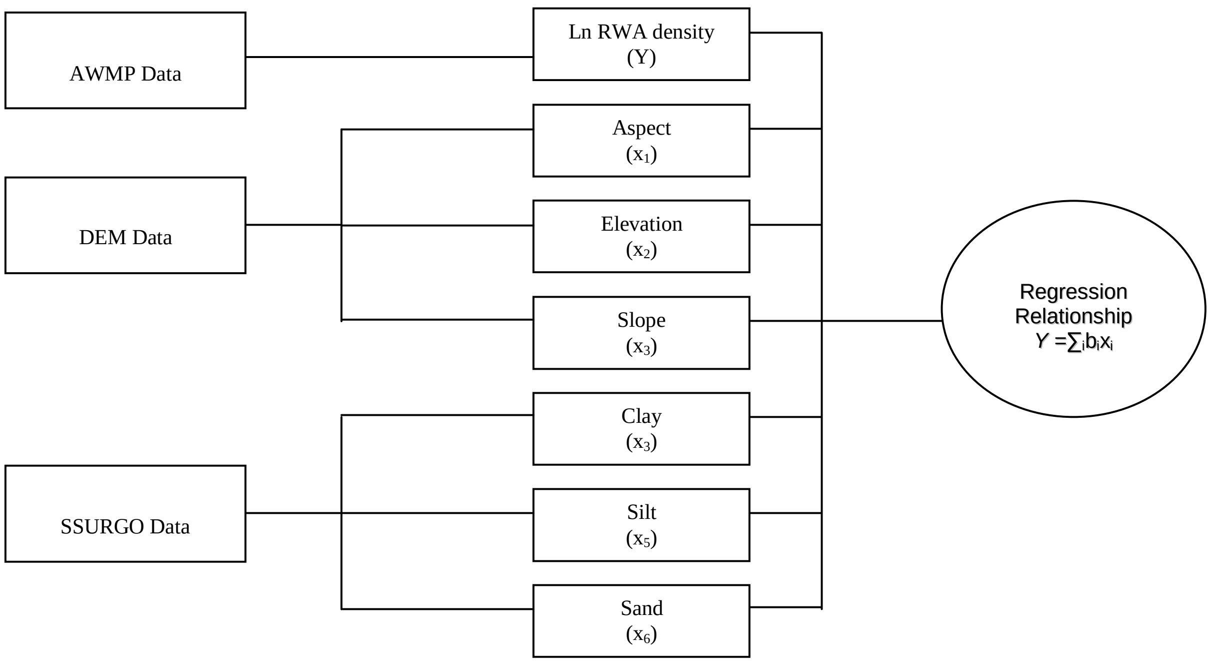

Figure 2. Schematic for the RWA population study

Results

The total number of observations used in this analysis was *N* =150. The means were: *Y* of 4.2594, aspect of 100.7 degrees, relative elevation of 0, slope of 3 %, and soil that was 18.82 % of clay, 38.51 % of silt, and 42.70 % of sand.

Table 3 lists the correlation coefficients for all pairs of variables used in the analysis and their significance at the 0.05 level. Variables such as Slope, Clay, Silt and Sand were significantly correlated to with *Y*. All these variables were positively correlated with *Y* except Silt. Aspect and Relative elevation were not statistically correlated with *Y*. Aspect was significantly correlated with Slope, Silt, and Sand. Aspect presented no significant correlation with Relative Elevation and Clay. Relative Elevation was not correlated with any other variable. Slope was significantly correlated with *Y*, Clay and Sand but not with Silt. Clay was positively related to *Y* (r = 0.200) and Slope (r = 0.267), and negatively to Aspect (r = -0.71) and Silt (r = -0.411). Sand was significantly positively related to *Y* and negatively related to Aspect, Slope and Silt. Sand was positively related with Clay but not significantly.

I explored four multiple regression models after assessing the relationship of each independent variable with *Y*. First, I entered all variables, Aspect, relative Elevation, Slope, Clay, and Sand together one time. Second, I used a forward stepwise multiple regression. Third, I entered all the variables with their squared values, together at one time, and fourth, I used a forward stepwise multiple regression analysis with all independent variables and their squared values. The results are summarized in table 4.

All multiple regressions have p-value less than 0.05, meaning that there was a statistically significant relationship between the variables at the 95 percent confidence level.

Model 1

In the model 1, the variables explained 25.14 percent of the variability of *Y*. Three variables, Aspect, Relative Elevation, and Clay were statistically significant. The equation of the fitted model and the significance of each variable are displayed in Table 5.

Model 2

Using stepwise regression in the second model, 24.20 percent of variation in *Y* was explained by Slope and Sand. Table 6 displays the equation of the fitted model and the statistical significance of each predictor.

Model 3

In this model, ten variables were entered, Aspect, Aspect squared, Relative Elevation Relative, Elevation squared, Slope, Slope squared, Clay, Clay squared, Sand, and Sand Squared. R-squared for this model is 36.60 percent. Six variables out of ten had a p-value greater that 0.05. These variables included Aspect, Aspect squared, Relative Elevation, Relative Elevation squared, Clay, and Clay squared. Slope, Sand and their squared value were significantly related to *Y*. The equation of the third fitted model and the statistical significance are shown in Table 7.

Model 4

The stepwise regression applied to all variables and their squared value in the fourth model explained 32.51 percent of variation of Y. Three variables were retained in the final model, Slope, Slope squared, and Sand squared. Table 8 displays the equation of the fitted model and the statistical significance of each variable.

Table 3. Correlation matrix (r) for all variables. Pairwise correlation between variables and their significance. The level of significance is 0.05. *s* indicates a relationship statistically significance, and *ns* a relationship not statistically significant

	LnRWA		*Aspect*		*ReElevation*		*Slope*		*Clay*		*Silt*		*Sand*
LnRWA	1.00												
Aspect	0.010	ns	1.00										
ReElevation	0.027	ns	0.002	ns	1.00								
Slope	0.320	s	0.174	s	0.055	ns	1.00						
Clay	0.200	s	-0.71	ns	0.038	ns	0.267	s	1.00				
Silt	-0.347	s	0.214	s	-.094	ns	0.100	ns	-0.411	s	1.00		
Sand	0.294	s	-0.204	s	0.086	ns	-0.225	s	0.020	ns	-0.92	s	1.00

Table 4. Coefficient of determination (r^2) for the four multiple regression models and the number of variables in each model.

Model	*Variables*	r^2	*# of Variables*
1	All variables together	25.14	5
2	Forward stepwise of all variables	24.20	2
3	All variables with their squared values	36.57	10
4	Forward all variables with their squared values	32.51	3

Table 5. Coefficients, *p*-values and significances for Model 1. The coefficients give a measure of the contribution of each variable to the model. A large value indicates that a unit change in the prediction has a large effect on the population density of RWA. The level of significance is 0.05. *s* indicates a relationship statistically significance, and *ns* a relationship not statistically significant

	Coefficients	*p-value*	*Significance*
Constant	1.73568	0.0007	s
Aspect	0.00054	0.6892	ns
ReElev	-0.19066	0.6693	ns
Slope	0.15274	0.0000	s
Clay	0.02175	0.2115	ns
Sand	0.03815	0.0000	s

Table 6. Coefficients, *p*-values and significances for Model 2. The coefficients give a measure of the contribution of each variable to the model. A large value indicates that a unit change in the prediction has a large effect on the population density of RWA. The level of significance is 0.05. *s* indicates a relationship statistically significance, and *ns* a relationship not statistically significant

Parameter	*Coefficients*	*p-value*	*Significance*
Constant	2.16766	0.00	S
Slope	0.164438	0.00	S
Sand	0.0381076	0.00	S

Table 7. Coefficients, *p*-values and significances for Model 3. The coefficients give a measure of the contribution of each variable to the model. A large value indicates that a unit change in the prediction has a large effect on the population density of RWA. The level of significance is 0.05. *s* indicates a relationship statistically significance, and *ns* a relationship not statistically significant

Parameter	*Coefficients*	*p-value*	*Significance*
Constant	3.25187	0.0000	s
Aspect	0.00100471	0.7979	ns
AspectSQ	-0.00000316	0.8314	ns
ReElev	-0.375614	0.4129	ns
ReElevSQ	-1.01175	0.1331	ns
Slope	0.337339	0.0002	s
SlopeSQ	-0.0170091	0.0061	s
Clay	0.107847	0.1985	ns
ClaySQ	-0.00218211	0.2998	ns
Sand	-0.0920048	0.0231	s
SandSQ	0.00156066	0.0010	s

Table 8. Coefficients, *p*-values and significances for Model 4. The coefficients give a measure of the contribution of each variable to the model. A large value indicates that a unit change in the prediction has a large effect on the population density of RWA. The level of significance is 0.05. *s* indicates a relationship statistically significance, and *ns* a relationship not statistically significant

Parameter	*Estimate*	*P-Value*	*Significance*
CONSTANT	2.50331	0.0000	S
Slope	0.396093	0.0000	S
SlopeSQ	-0.0193027	0.0010	S
SandSQ	0.000520102	0.0000	S

Discussion and Conclusion

The RWA has significantly affected the agricultural economy in the US Great Plains and Rocky mountains agricultural regions since 1986. Understanding the relationship between the RWA population density and abiotic factors aids efforts in improved pest management decision making. The findings of this study supports Begon's et al. (1990) statement that abiotic factors such as climate, topography, and soil influence organisms. Weather variables were not among the abiotic factors considered in this study because it is unlikely that weather affects the spatial distribution of RWA in fields. Weather more likely determines the overall population density at the field and at the broader spatial scales. However, weather has a significant effect on RWA population dynamics as demonstrated in other investigations (e.g. Legg and Brewer, 1995).

The present study demonstrated a relationship between RWA population density and topographic and edaphic factors. Slope and sand showed statistically significant relationships with RWA density in the four models explored. I expected that Slope and Sand would explain variation of RWA population density. The surprise was that other topographic and edaphic variables such as aspect, relative elevation, and clay did not show predictive ability. Out of the four regression models explored, model 2 and 4 contained variables such as slope and sand that statistically explained 24.20 and 32.51% of the variability of Y. Model 2 showed that slope and sand had a linear relationship with Y. As things in the natural environment are not always linear, model 4 showed a nonlinear relationship between slope, sand and the density of RWA. Model 4 revealed that the population density of RWA increased with slope and sand and decreased when the patch of the wheat field reaches a certain level of slope.

This finding supports the work of Merill (2007) who found five predictor variables to elucidate variation in RWA density. The variables Merill (2007) found were: slope, wavelength (Band 3 of Landsat 7 ETM), NDVI, relative elevation, and soil type. For Merill (2007) relative elevation was not a strong predictor for several reasons that included the fact that low areas could shelter from wind effects or could be areas of snow accumulation. The geographic orientation of the wheat field is important for the variation of RWA population density. Hammon and Peairs (1992) found that RWA were distributed throughout fields with east-west furrows, but the highest RWA infestations were located on south-facing slopes. In this study, aspect was not related to RWA population density.

Few studies explored the relationship between RWA population density and abiotic factors such as topographic or edaphic factors. Studies carried out on different aphid species showed that variability of aphid population density was related to geographic position, topography, aspect and size of the field. Foster et al. (2004), investigating the relationship of pest-field characteristics in the United Kingdom, analyzed the incidence of the density of two species of cereal aphids in four soil classes: sandy, loam, clay loam, and clay. They found that the population density of aphids was different across the four classes of soil texture. One of the aphids, *Rhopalosiphum padi*, was more abundant on loamy soils and least abundant on clay, while the other aphid, *Sitobon avenae*, was more abundant on sandy soils and least on clay loam. Analyzing the effect of aspect, Foster et al. (2004) found higher population density of *R. padi* on fields that were facing southwest, while Auslander et al. (2003) in another study on the effects of aspect on *Pistacia lentiscus*, a shrub native to Mediterranean regions, found higher population densities of the aphid *Aploneura lentisci* in south facing slopes. Slope itself in Auslander et al. (2003) study did not affect the population density of aphids. The grain and extent of both studies differed. Foster et al (2004) investigated on sampling areas that were 0.3 ha and Auslander et al. (2003) used 100 ha.

In my study, I used the RWA population density that was collected from a 5 by 5 grid sampling points that varied in size according to the size of the wheat field. These data were intersected with SSURGO data and 10-meter grain size of DEM data from which aspect and slope were derived. SSURGO data were derived from map digitization and information from aerial photography. The soil surveys were mapped based on 1.2 hectare minimum units with delineations that depicted dominant soils. The scale of the map digitization process and of the soil survey could introduce some discrepancy that could make small areas at the field scale to not be observable in the data. This problem could be evident in data used in this study. The spatial resolution of SSURGO and DEM data limit their value for studies such as mine. How well the soil sampling points could be checked, how accurate were the sampling points at the boundaries between two types of soil texture, how precise were sampling points in the 10-meter grain size of DEM data? I suggest that further studies use topographic and edaphic data that are collected at each sampling point instead of relying on SSURGO and DEM data that contain unknown levels of accuracy.

The results of this study are encouraging and agree with previous studies by Merill (2007) and Hammon and Peairs (2003) in the way that the population density of RWA is related to topographic and edaphic factors. Slope and sand are variables that explained the variability of the RWA population. These results could be improved if the topographic and edaphic variables were measured more accurately at each sampling point. Furthermore, measuring a wider range of topographic and edaphic variables might also increase prediction of variation in RWA population density within wheat fields.

References

Adisu, B., and B. Freier. 2003. The potential of biocontrol agents for control of *Diuraphis noxia* (Homoptera: Aphididae) in spring barley in the central highlands of Ethiopia. Biological Agriculture and Horticulture 21:35-51.

Auslander, M., E. Nevo, and M. Inbar. 2003. The effects of slope orientation on plant growth, developmental instability and susceptibility to herbivores. Journal of Arid Environments 55(3):405-416.

Begon, M., J. L. Harper, and C. R. Townsend. 1996. Ecology: Individuals, populations and communities. Blackwell Scientific Publications, London.

Bosque-Perez, N.A., J. B. Johnson, D. J. Schotzko, and L. Unger. 2002. Species diversity, abundance, and phenology of aphid natural enemies on spring wheats resistant and susceptible to Russian wheat aphid. BioControl 47(6):667-684.

Botha, J., and H. Hardie. 2000. Diuraphis noxia: Grain-guard threat data sheat for the wheat industry in Western Australia. 2-35. Department of Agriculture and Food , Government of Western Australia, Perth.

Cocu, N., M. D. A. Rounsevell, K. Conrad, and R. Harrington. 2005. Analysis of spatial patterns at a geographical scale over north-western Europe from point-referenced aphid count data. Bulletin of Entomological Research 95(1):47-56.

Dorry, H.R., and M. T. Assad. 2001. Inheritance of leaf shape and its association with chlorosis in wheat infested by Russian wheat aphid (*Diuraphis noxia*).Journal of Agricultural Science 137: 169-172.

Foster, G.N., R. Harrington, S. Blake, S. J. Tones., and I. Barker. 2004. Occurrence of barley yellow dwarf virus in autumn-sown cereal crops in the United Kingdom in relation to field characteristics. Pest Management Science 60(2):113-125.

Gilchrist, L. I., R. Rodriguez, and P. A. Burnett. 1984. The extent of freestate and *Diuraphis noxia* in Mexico. Pp157-163. in Burnett, P. A. and E. Cuellar (Eds.), Barley Yellow Dwarf. Proceedings of a Workshop, 6-8 December, 1983, CIMMYT, Mexico.

Grimm, L. G., and P. R. Yarnold. 1995. Reading and Understanding Multivariate Statistics. Washington, D.C.: American Psychological Association.

Grossheim, N. A. 1914. The barley aphid (*Brachylocus noxius*) Mordvilko). Trudy estest. –istor. Muz.,,Simferopol 3:35-78. In Russian:English summary in Rev. Appl. 3:307-308.

Halbert, S.E., and M.B. Stoetzel. 1998. Historical overview of the Russian wheat aphid (Homopter: Aphididae). p. 12–30. *In* S.S. Quisenberry, and F.B. Peairs (ed.) Response Model for an Introduced Pest–The Russian Wheat Aphid. Entomological Society of America. Latham, MD.

Hammon, R.W.,and F. B. Peairs. 1992. Distribution of overwintering Russian Wheat Aphid (Homoptera: Aphididae) in furrow irrigated small grains in western Colorado. Journal of Econ. Entomol. 85:2452-2458.

Hein, G. L., F. P. Baxendale, J. B. Campbell, A. F. Hagen, J. A. Kalisch. 1998. Russian wheat aphid. File G936 under: INSECTS AND PESTS C-31, Field Crops. Cooperative Extension, Institute of Agriculture and Natural Resources. University of Nebraska, Lincoln, NE.

Hughes, R. D., and G. F. Maywald. 1990. Forcasting the favourableness of the Australian environment to the Russian wheat aphid, *Diuraphis noxia* (Homoptera:Aphididae), and its potential impact on Australian wheat yield. Bulletin Entomol Res 80:165-175.

Jones, J. W., J. R. Byers, R. A. Butts, and J. L. Harris. 1989. A new pest in Canada: Russian wheat aphid, *Diuraphis noxia* (Mordvilko) (Homoptera:Aphididae). The Canadian Entomologist: 623-624.

Legg, D. E., and M. J. Brewer. 1995. Relating within-season Russian wheat aphid (Homoptera:Aphididae) population growth in dryland witner wheat to heat units and rainfall. Journal of Kanzas Entomological Society 68:149-158.

Mattson, W. J., and R. A. Haack. 1987. The role of drought stress in provoking outbreaks of phytophagous insects. Pages 365-407 in P. Barbosa and J. C. Schultz, editors. Insect outbreaks. Academic Press, New York, New York, USA.

Merill, S. C. 2007. Overwintering ecology of Russian wheat aphid, *Diuraphis noxia*, (Kurdjumov) in eastern Colorado. PhD Dissertation. Colorado Sate University, For Collins, CO.

Puterka, G. J., J. D. Burd, D. Porter, K. Shufran, C. Barker, B. Bowling, and C. Patrick. 2007. Distribution and diversity of Russian wheat aphid (Hemiptera : Aphididae) biotypes in north America. Journal of Economic Entomology 100(5):1679-1684. Published: OCT 2007.

Orwing, D. A, D. R. Foster, and D. L. Mausel. 2002. Landscape patterns of hemlock decline in New England due to the introduced hemlock woolly adelgid. Journal of Biogeography 29(10-11):1475-1487.

Riedell, W. E. 1989. Effects of Russian wheat aphids infestation on barley plant response to drought stress. Physiologia Plantarum 77:587-592.

Reviriego, M.E., L. R. Descamps, A. A. Ferreroy, and A. A. Suarez. 2004. Field efficacy and laboratory toxicity tests of insecticides against Diuraphis noxia (Homoptera: Aphididae). International Pest Control 46 (5):260-262.

Robinson, J. 1992. Russian wheat aphid: a growing problem for small-grain farmers. Outlook on Agriculture 21:57-61.

Sokal, R. R., and F. J. Rohlf. 1981. Biometry: The Principles and Practice of Statistics in Biological Research. Second Edition. W.H. Freeman and Co., New York.

Saheed, S. A., L. Liu, L. Jonsson, and C. E. J. Botha. 2007. Xylem – as well as phloem – sustains severe damage due to feeding by the Russian wheat aphid. South African journal of botany 73(4):593-599.

Starý, P. 1999. Parasitoids and biocontrol of Russian wheat aphid, Diuraphis noxia (Kurdj.) expanding in central Europe. Journal of Applied Entomology 123:273-279.

Stoetzel,M. B. 1987. Information on and identification of *Diuraphis noxia* (Homoptera: aphididae) and other aphid species colonizing leaves of wheat and barley in the United States. Journal of Economic Entomology 80:694–704.

Thomas, J., G. Hein, D. Baltensperger, L. Nelson, and S. Haley. 2002. Managing the Russian Wheat Aphid with resistant varieties. File NF307 under: Insect and Pests. C-5, Field Crops. Nebraska Cooperative Extension. University of Nebraska, Lincoln, NE.

Walters, M. C. 1984. Progress in Russian wheat aphid (*Diuraphis noxia* Mordvilko) Research in Republic of South Africa. South African Department of Agriculture, Technical Communication 191, Pretoria.

Walters, M. C., F. Penn, F. Du Toit, T. C. Botha, K. Aabersberg, P. H. Hewitt, and S. W. Broodryk. 1980. The Russian wheat aphid. Farming in South Africa, Leafl. Ser., Wheat G3:1-6.

Warner, R. M. 2008. Applied Statistics: from bivariate through multivariate techniques. Sage Publications. Los Angeles, CA.

Webster, J.A., R. Treat, L. Morgan, and N. C Elliott. 2000. Economic impact of Russian wheat aphid and green bug in the western United States 1993-94, 1994-95, and 1997-98. USDA, Agricultural Research Service Report, PSWCRL Rep. 00-001, Plant Science and Water Conservation Research Laboratory, Stillwater, OK.

CHAPTER IV

UTILIZATION OF AIRBORNE MULTISPECTRAL IMAGERY TO DETECT STRESS INDUCED TO WHEAT PLANTS BY THE RWA

Abstract

The Russian wheat aphid (RWA), *Diuraphis noxia*, is one of the most significant pests that damages winter wheat *Triticum aesticum* and barley, *Hordeum vulgare*. This pest was first identified in the United States in 1986. Since then, the RWA spread rapidly, from Texas to the Rocky Mountains into Canada. The economic loss to the small grain industry caused by the RWA is estimated at over one billion dollars. The objective of this study was to determine the potential of using remote sensing technology and a spatial pattern recognition approach to identify and spatially quantify RWA infestations within wheat fields. Data used included multispectral imagery acquired April - May 2005, and 2007, in the vicinity of Boise City, OK. Wheat fields were damaged by three types of stress factors: RWA, Drought and Cultural Issues. ERDAS Imagine software was used to process and analyze images. FRAGSTATS was used to quantify spatial pattern. Twenty-four metrics were computed at class level for each stress factors. The t-

test revealed that nine landscape metrics were significantly different among the three types of wheat plant damage. The combination of multispectral data and landscape metrics made it possible to characterize RWA infested patches from stressed patches caused by other factors. The detection and quantification of wheat field stress may help in mapping and differentiating RWA infestation, and may also have implications for site-specific pesticide application and for monitoring systems to control RWA infestations.

Introduction

The Russian wheat aphid (RWA), *Diuraphis noxia* (Mordvilko) (Hemiptera:Aphididae), is one of the most significant pests that damages winter wheat *Triticum aesticum* and barley, *Hordeum vulgare* (Puterka et al., 2007). In the United States, the RWA was first identified near Muleshoe, TX in 1986 (Morisson and Peairs, 1998). Since then, the RWA has spread rapidly, from Texas to the Rocky Mountains into Canada (Thomas et al., 2002). The economic loss to the small grain industry caused by the RWA is estimated at over one billion dollars (Archer and Bynum, 1992; Morrison and Peairs, 1998; Webster et al., 2000).

The RWA invades wheat fields from the stage of plant emergence to harvest. It feeds on young wheat leaves causing symptoms that include longitudinal chlorotic streaking and leaf rolling (Webster et al., 1987). The RWA induces stress to the wheat crop by damaging plant foliage, which lowers the greenness of the plant and affects wheat crop productivity (Burd et al., 1998; Miller et al., 1994). The loss of productivity can be catastrophic for farmers who usually rely mainly on chemicals to control the RWA infestation.

Remote sensing technology has shown its importance in detecting stress to vegetation (Adams et al., 1999; Metternicht, 2003). It is possible to use remote sensing technology to detect wheat fields that need treatment to control the RWA. Stress in plants may be a mixture of several stressors that may include drought, nutrient deficiency, pests, diseases, etc.

Remote sensing offers the possibility to identify RWA infestations within fields comparatively cheaply (Mirik et al., 2007). However, the question arises, how to spatially identify and quantify stress induced by RWA from other stress causing factors. Since remote sensing technology can be used to detect crop stress it may be possible to use this technology in combination with a spatial pattern recognition approach to detect and quantify infestations by RWA in wheat. A spatial pattern recognition approach could use landscape metrics to quantify spatial pattern in an ecosystem.

Landscape metrics are indicators used to describe the structure and pattern of a landscape. Landscape metrics quantitatively represent landscape pattern. The quantification of the landscape pattern is not only useful for understanding the effect of pattern on ecological process but also for documenting temporal changes in a landscape or differences between two or more landscapes (Turner et al., 2001). Indeed, landscape metrics are used to compare ecological quality across the landscape (Riitters et al., 1995), across scales (Frohn, 1997) and to track change that may occur in landscape pattern through time. Each landscape metric describes a particular characteristic of landscape pattern. The behavior of the metrics is known and measures values distributed over the full range of the landscape.

This study is complementary to research described in chapter 3, which investigates the relationship between RWA and abiotic factors. The objective of this study is to determine the potential of the combination of remote sensing technology and a spatial pattern recognition approach to identify and spatially quantify RWA infestations within wheat fields. Remote sensing has been used for decades to survey vegetation cover. Spatial pattern recognition approach was used in combination with remote sensing to quantify the spatial pattern of RWA infestations on wheat fields.

The findings of this study progress towards practical methods to detect RWA infested wheat fields using multispectral imagery. Ultimately, the goal is to provide growers and managers with an immediately available, non-destructive, inexpensive method to detect RWA infestations, and the ability to apply site-specific pest control practices when and where needed. Such an approach to pest management could increase growers' profits and improve environmental and human health.

Materials and Methods

The aim of this section is to present the procedure used to collect, analyze and interpret data collected for this study. The overall procedure is outlined in the Figure 1, which presents the flow chart of the methodology used in this study.

Study area

The study area was located in the vicinity of Boise City located at 36º.73' N, -102º.51' W, in Cimarron County in the panhandle of Oklahoma. The area has an annual mean temperature of 13.05º Celsius, and an annual average precipitation of 470.6 millimeters. The month of June is the wettest of the year with an average of 72.2

millimeters. In this region, wheat is planted in September – October and harvested in June – July each year.

Data acquisition

The data used in this study were collected in April - May 2005, and 2007. Data collected consist of Global Positioning System coordinates (GPS) and multispectral images. The study plots were rectangular areas of 200 meters by 200 meters within wheat fields. GPS data were ground control points (GCPs) or coordinate points within study plots. GPS data were used for pilot orientation during the acquisition of imagery, and to help in image geometric correction and classification.

The process for collecting data required first, finding fields with damaged wheat plants. Then, GCPs were recorded using an HP iPAQ handheld GPS receiver (Figure 2). These GCPs were used by the pilot to orient the airplane above the study wheat fields. At the perimeter of each selected wheat field, silver tarps were positioned 200 meters apart to define the study plot before imaging. The coordinates of the center of each tarp were recorded to be used when rectifying and georeferencing each image (Figure 3 & 4). Homogeneous spots of damaged wheat plants were also recorded inside of fields to help in the image classification process.

Multispectral image data for each selected wheat field were acquired using the MS3100-CIR, a multispectral camera customized by Duncan Tech. The camera acquires (1392 x 1040 pixels) high resolution images in three co-registered channels. The camera uses a color separating prism with three Charge Coupled Device (3-CCD) sensors that cover three channels: near infrared, red and green (Channel1, Channel 2 and Channel 3), centered at 800, 650, and 550 nanometers with bandwidths of 65, 40, and 40 nanometers of the spectrum (Anonymous, 2008). The MS3100-CIR camera was mounted NADIR in the fuselage of a Cessna 172 aircraft. This camera used a progressive scan to capture very clear images that were saved to a computer hard drive in the .tif format (Figure 9:abcd).

Image processing and analysis

I used ERDAS Imagine software (version 8.6) to process and analyze multispectral images. Through the image processing and analysis, image data were manipulated to detect RWA infestations and delineate their pattern and spatial distribution on wheat fields. The combination of the three channels was used in the image processing. Figure 1 illustrates the overall image processing, which involved preprocessing, processing and analyzing images collected over wheat fields.

Data preprocessing helped identify any problems that arose during data collection that could reduce the effectiveness of the intended analysis or render the data unusable. During image prepocessing, image data were geometrically verified, and corrected using the GCPs data. After the correction, I registered the images using the 2003 National Agricultural Imagery Program (NAIP) data available online at the USDA-Farm Service Agency. Each image was projected onto a plane and made to conform to a map projection system or Universal Transverse Mercator (UTM). The process made each image conform to other images and involved rearrangement of the input pixels onto a new grid, which was conformed to the desired map projection and coordinate system. After each wheat field image was rectified, the output of this process was used in image processing.

Mapping the wheat field to detect the spatial distribution of stress induced by RWA required classifying the multi-spectral image of each field selected. In this classification process, pixels of each image were categorized into classes. The categorization was based on the spatial pattern of patches of damaged wheat plants that differed from the surrounding wheat. Classes were based on the difference in spectral reflectance between healthy and damaged wheat plants. Initially, two classes were anticipated for each image: Healthy and Stressed classes. The first class was Healthy Wheat, where wheat plants were not damaged. The second class, Stressed included RWA, Drought, or Cultural Issues, depending on the cause that induced the plant damage. The healthy wheat class was homogeneous areas that were not infested or damaged, by RWA, drought or any cultural problem. The RWA class was areas where wheat plants were infested by RWA. The presence of RWA was evident on these patches. The Drought class contained wheat plants that were affected by drought. The Cultural Issues class had wheat plants with one or more concerns related to site preparation including tillage, plant germination, or fertilization.

Unsupervised classification was used to aggregate the pixels into natural spectral groupings or clusters present in each image. Twenty classes were selected with an approximate true color technique. Pixels reflecting healthy wheat plants were masked to separate healthy wheat plants from damaged or stressed plants. The masking process was repeated iteratively until all areas with healthy plants had been separated. The remaining pixels contained areas where wheat plants were damaged by RWA, drought, or planting issues.

Each image was then recoded into two classes. The post classification process included a GIS filtering, the neighborhood analysis that was based on the majority of pixels in a given class, to clean up pixels that were not correctly classified. The product of the classification process was a thematic raster map that displayed healthy wheat and patches damaged by RWA infestation, drought, or cultural Issues.

Quantification of stress pattern

After classifying each image, I computed landscape metrics on the basis of the classified multispectral images created using the process described in the previous section. This process allowed quantifying the spatial pattern of RWA infestation. Metrics are usually computed at three levels: patch, class and landscape (see Table 1). In the present study class level metrics were mainly considered. A patch was defined as the smallest, homogeneous area that differed from its surroundings and that had identifiable boundaries. All patches of a particular class within a classified image compose a class, which in this study were patches of healthy wheat plants or damaged wheat plants (RWA, Drought and Cultural Issues), and all classes comprise a landscape, which in the present study was the entire 200 x 200 meters study plot within a particular wheat field.

I used FRAGSTATS (version 3.3), a public domain computer program developed by McGarigal and Marks (1995), to quantify the landscape pattern. The program is available online and requires a little technical training. It generates an array of metrics at the patch, class, and landscape level. This study focused on class level, and 24 landscape-class metrics were generated: Class Area (CA), Percentage of Landscape (PLAND), Number of Patches (NP), Patch Density (PD), Largest Patch Index (LPI), Landscape Shape Index (LSI), Area-Weighted Mean Patch Area Distribution (AREA_AM), Area-Weighted Mean Radius of Gyration Distribution (GYRATE_AM), Normalized Landscape Shape Index (nLSI), Area-Weighted Mean Shape Index (SHAPE_AM), Area-Weighted Mean Perimeter-Area Ratio (PARA_AM), Area-Weighted Mean Fractal

Dimension Index (FRAC_AM), Area-Weighted Mean Related Circumscribing Circle, (CIRCLE_AM), Area-Weighted Mean Contiguity Index (CONTIG_AM), Perimeter-Area Fractal Dimension (PAFRAC), Area-Weighted Mean Proximity (PROX_AM), Area-Weighted Mean Euclidean Nearest-Neighbor Distance (ENN_AM), Clumpiness Index (CLUMPY), Percentage of Like Adjacencies (PLADJ), Aggregation Index (AI), Splitting Index (SPLIT), Effective Mesh Size (MESH), Patch cohesion index (COHESION), and Connectance Index (CONNECT). The 24 metrics could be grouped into five general categories: area\density\edge, shape, isolation\proximity, contagion\interpersion, and connectivity (Table 1). A brief description of each landscape metric was provided in Table 2. More detailed information about the landscape metrics can be found in McGarigal et al. (2002). The software SPSS (version 16) was used to compare pairs of landscape metrics, using the *t*-test to determine if differences existed between the three types of patch (RWA, Drought and Cultural Issues) in the value of a particular metric. $P<0.05$ was considered as evidence of significance.

Table 1. Landscape metrics at patch, class and landscape levels. The table illustrates different landscape metrics based on the landscape patterns and the level of the analysis. Contagion/Interspersion and Connectivity cannot be analyzed at patch level.

Area\Density\Edge	***Shape***	***Isolation\Proximity***	***Contagion\Interspersion***	***Connectivity***
		Patch Level		
AREA	*PARA*	*PROX*		
PERIM	*SHAPE*	*ENN*		
GYRATE	*CIRCLE*			
	CONTIG			
		Class Level		
CA	*PAFRAC*	*PROX_AM*	*CLUMPY*	*COHESION*
PLAND	*PARA_AM*	*ENN_AM*	*PLADJ*	*CONNECT*
NP	*SHAPE_AM*		*AI*	
PD	*CIRCLE_AM*		*DIVISION*	
LSI	*CONTIG_AM*		*SPLIT*	
AREA_AM	*FRAC_AM*		*MESH*	
GYRATE_AM				
		Landscape Level		
TA	*PAFRAC*	*PROX_AM*	*CONTAG*	*COHESION*
NP	*SHAPE_AM*	*ENN_AM*	*PLADJ*	*CONNECT*
PD	*PARA_AM*		*DIVISION*	
LPI	*CIRCLE_AM*		*SPLIT*	
AREA_AM	*CONTIG_AM*		*MESH*	
			AI	

Table 2. List of landscape metrics at class level, computed from classified images using FRAGSTATS (Description adapted from McGarical and Marks, 1995)

Patterns	***Metrics***	***Abbreviations***	***Units***	***Description***
Area\ Density\ Edge	Class Area	*CA*	*Hectares*	The measure of the field composition, measures how much of the field is comprised of a particular patch type
	Percentage of Landscape	*PLAND*	*Percent*	The quantification of the proportional abundance of each patch type in the landscape (wheat field).
	Number of Patches	*NP*	*No units*	The total number of patches in the landscape
	Patch Density	*PD*	*Unit per area*	The number of patches per unit area
	Largest Patch	*LPI*	*Percent*	The ratio of the area of the largest patch to the total area of landscape
	Landscape Shape Index	*LSI*	*No units*	The measure of class aggregation or clumpiness
	Area-Weighted Mean Patch Area Distribution	*AREA_AM*	*Hectares*	The sum, across all patches of the corresponding patch type, of the corresponding patch metric value multiplied by the proportional abundance of the patch.
	Area-Weighted Mean Radius of Gyration Distribution	*GYRATE_AM*	*Meters*	The measure of the measure of class extent, involves the mean distance (m) Between each cell in the patch and the patch centroid.
	Normalized Landscape Shape	*nLSI*	*No units*	The measure of class aggregation or clumpiness
Shape	Area-Weighted Mean Shape	*SHAPE_AM*	*No units*	The ratio of patch perimeter to the minimum perimeter for the maximally compact patch of the same patch area across the landscape
	Area-Weighted Mean Perimeter-Area Ratio	*PARA_AM*	*No units*	The ratio of patch perimeter to area measuring shape complexity across the landscape
	Area-Weighted Mean Fractal Dimension	*FRAC_AM*	*No units*	The ration across the landscape of the 2 times logarithm of patch perimeter to logarithm of patch area, that measures shape complexity across a range of spatial scales.
	Area-Weighted Mean Related Circumscribing Circle	*CIRCLE_AM*	*No units*	The measure of the linearity or elongation of patches. 0=CIRCLE<1
	Area-Weighted Mean Contiguity	*CONTIG_AM*	*No units*	The measure of the spatial connectedness, or contiguity, of cells within a grid-cell patch to provide an index of patch boundary configuration and thus patch shape
	Perimeter-Area Fractal Dimension	*PAFRAC*	*No units*	The measure of shape complexity across a range of spatial scales (spatial sizes). 1 = PAFRAC = 2
Isolation\ Proximity	Area-Weighted Mean Proximity	*PROX*	*No units*	The ratio of the sum of patch areas to the nearest edge-to-edge distance squared between patches in a specific radius
	Area-Weighted Mean Euclidean Nearest-Neighbor Distance	*ENN_AM*	*Meters*	The measure of the shortest straight-line distance between the focal patch and its nearest neighbor of the same class.
Contagion\ Interspersion	Clumpiness Index	*CLUMPY*	*No units*	The measure of proportional deviation of adjancies in class expected under a spatially random distribution
	Percentage of Like Adjacencies	*PLADJ*	*No units*	The measure of proportion of cell adjacencies involving the same class
	Aggregation Index	*AI*	*Percent*	The measure of the frequency with which different pairs of patch types (including like adjacencies between the same patch type)
	Splitting Index	*SPLIT*	*No units*	The ration of the total landscape area to the sum of patch area across all patches of same type
	Effective Mesh Size	*MESH*	*Hectares*	The measure of the size of the patches when the corresponding patch type is subdivided into patches
Connectivity	Patch cohesion index	*COHESION*	*No units*	The measure of the physical connectedness of the corresponding patch type
	Connectance Index	*CONNECT*	*Percent*	The measure of the maximum possible connectance given the number of patches

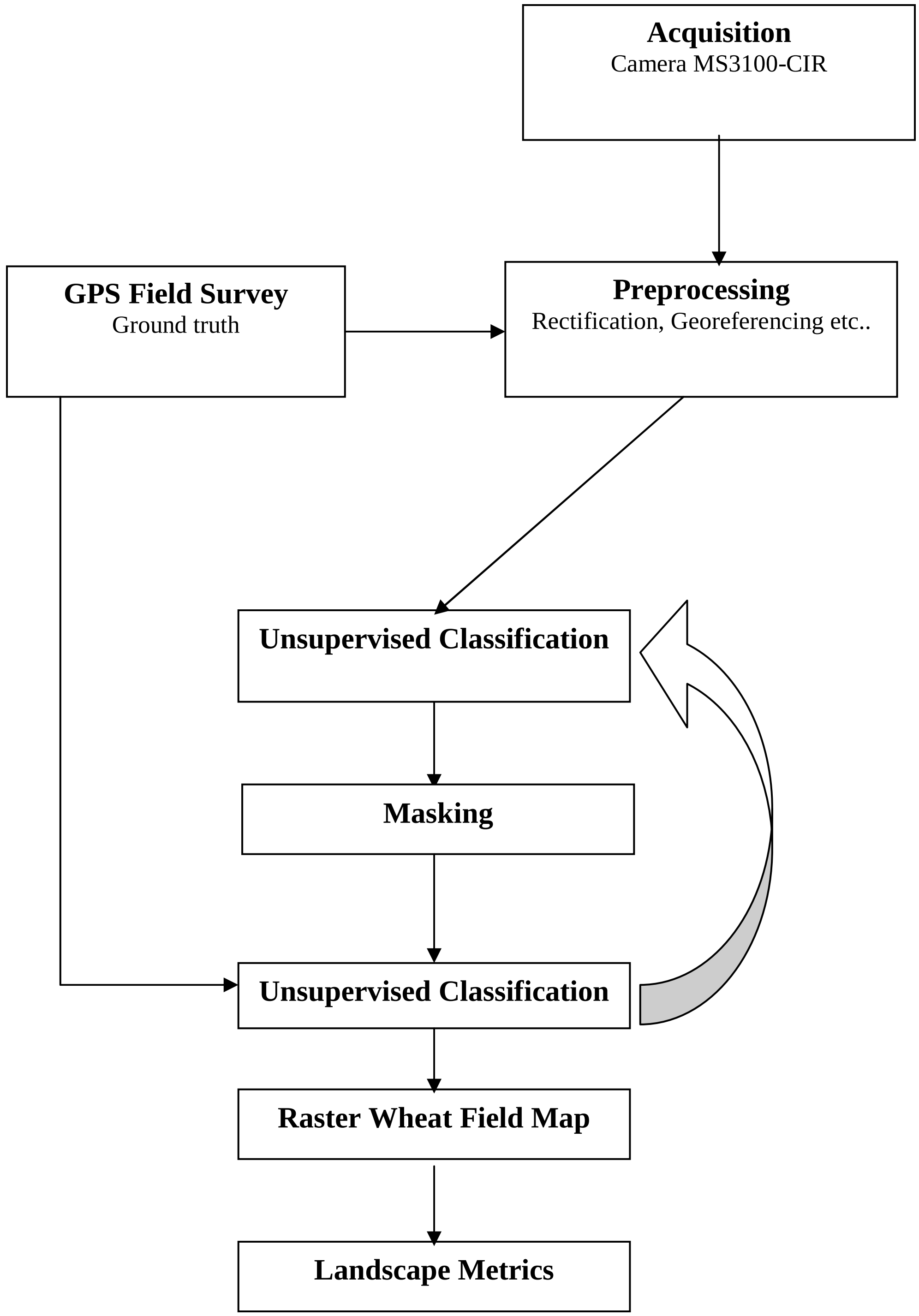

Figure 1. Flow chart of image analysis

Figure 2. HP iPAQ handheld GPS receiver unit used for data acquisition

Figure 3. GCPs data acquisition

Figure 4. Tarp used for GCPs

Figure 5. GPS coordinate data acquisition

Figure 6. Aircraft used for image collection

Figure 7. Camera port under fuselage aircraft

Figure 8 Duncan Tech camera used for image acquisition

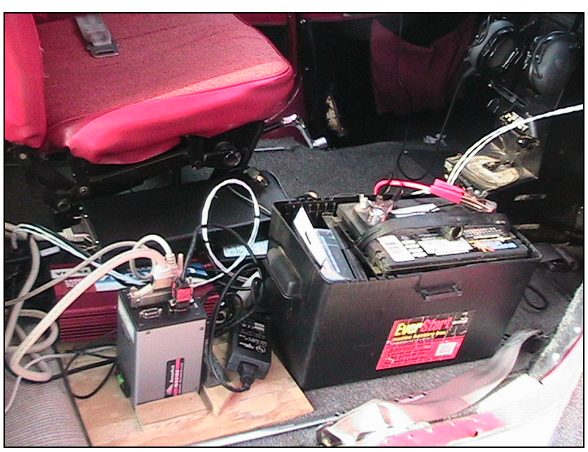

Figure 9. Imaging equipment inside the aircraft

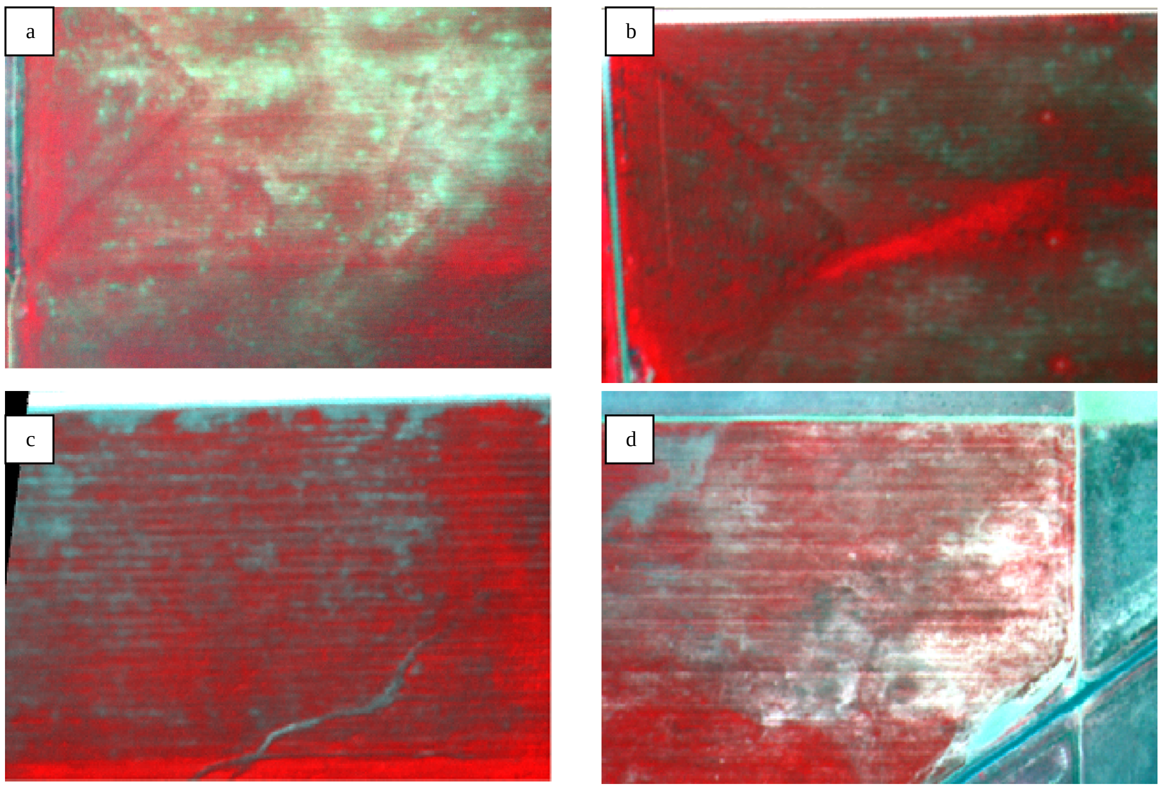

Figure 9. Raw image collected on wheat fields: a) and b RWA: c) cultural issues and d) drought

Results

Initial visual inspection of the multi-spectral images revealed that wheat plants were damaged predominately by three types of stress that originated from RWA infestation, drought and cultural issues. Areas in wheat fields that were damaged by RWA infestation (Figure 9 a, and b) present a particular aspect of speckles, somewhat mealy, mottled random spots with small contrasting patches. Areas damaged by drought (Figure 9 d), present large spots that seem to be randomly distributed. Cultural issues are displayed as linear patterns distributed on the wheat field.

The classification of the subset of each multi-spectral image is presented in Figure 10 that display (Figure 10 a, and b) the spatial pattern of RWA infestation. It shows patches of RWA infestation in a wheat field. The patches of RWA infestation have a particular configuration that looks like a constellation shape seen from the air. RWA infestation presents an arrangement that is specific and unique, formed with connected dots that tend to occur in a large homogenous group. The RWA infestation pattern visually appears to differ from the other types of damage.

Wheat damaged by drought is displayed in Figure 10 d. Drought spatial pattern presents several large patches of damaged wheat plants that are linearly connected to dots along the planting lines. Wheat fields damaged by cultural issues present several dots that are connected linearly, along the planting lines.

The classified images were used to generate landscape metrics of each wheat field.

The results of the Class level spatial quantification, from FRAGSTATS 3.3, for each type of stress are displayed in Table 3. Figure 10 presents a visual comparison of each metric.

The mean of Class Area of patches affected by drought were 1.24 ha (Table 3). This mean is larger than patches affected by RWA (0.88 ha) and cultural issues (0.26 ha). The Normalized Landscape Shape Index (nLSI) for patches affected by drought (0.30) was smaller than the nLSI affected by RWA (0.45), and Cultural Issues (0.59). Considering Shape metrics, PARA_AM for patches affected by RWA (22234.04) was smaller than for patches affected by Drought (24313.62) and Cultural Issues (44268.62). The mean of PROX_AM for patches affected by RWA (48.73) was slightly greater than the mean of patches affected by Drought (48.53) and considerably greater than patches affected by Cultural Issues (23.92). The ENN_AM for RWA was 1.83 meters, which was greater than the ENN_AM for patches affected by Cultural Issues (1.26 meters) and by Drought (1.16 meters). Considering the contagion metrics, the PLADJ for Drought was 70.02 percent, and greater than the PLADJ for patches affected by RWA (54.12 %) and by Cultural Issues (40.70 %). The connectivity metrics presented an opposite situation between COHESION and CONNECT. Patches affected by Drought had Cohesion metrics that were higher than both types of stress, while the CONNECT metric for Drought was lower than for the other types of stress.

Nine landscape metrics showed significant differences among the three types of stress to wheat plants (Table 5). Four landscape metrics, CA, ENN_AM, COHESION, and CONNECT differed significantly between stress induced by RWA and stress induced by drought. Four others, nLSI, PARA_AM, PLADJ and AI metrics differed significantly when comparing stress induced by RWA to stress induced by Cultural Issues. PROX_AM was the single landscape metric that significantly differed when comparing stress induced by Drought to stress induced by Cultural Issues. Statistical comparisons for each landscape metric were applied to determine whether differences existed in the value of each metric among the three types of stress. Out of 24 landscape metrics computed, 9 showed a significant statistical difference (Table 4). Landscape metrics that showed a statistically significant difference where CA, nLSI, PARA_AM, PROX_AM, ENN_AM, PLADJ, AI, COHESION, and CONNECT.

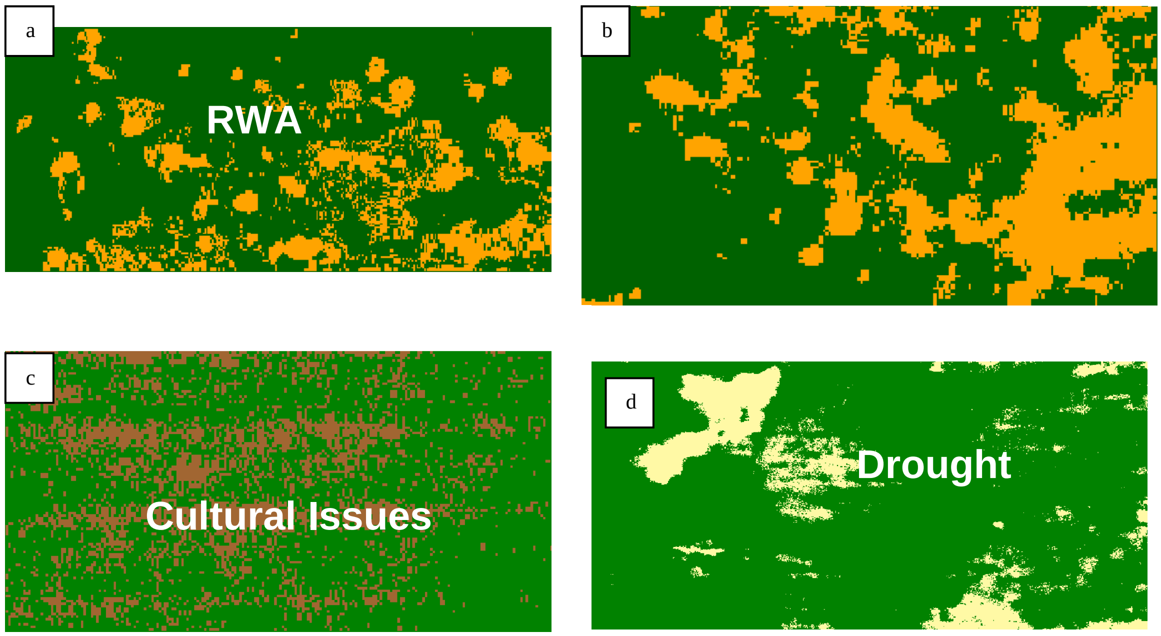

Figure 10. Classified image of wheat fields: a) and b RWA, c) Cultural Issues, and d) Drought.

Table 3. Summarizes the mean of each landscape metrics at class level, computed from FRAGSTATS for the three type of stress that damage wheat field (McGarical and Marks, 1995).

Patterns	***Metrics***	***Stressors***		
		RWA	***Drought***	***Cultural Issues***
Area\Density\Edge	*CA*	0.88	1.24	0.26
	PLAND	23.35	23.13	16.90
	NP	1121.75	1451.33	1725.00
	PD	32243.77	27067.53	113328.20
	LPI	1.86	9.15	1.65
	LSI	50.80	61.32	55.60
	AREA_AM	0.016	0.400	0.003
	GYRATE_AM	14.62	26.03	2.82
	nLSI	0.45	0.30	0.59
Shape	*SHAPE_AM*	3.98	4.42	3.11
	PARA_AM	22237.04	24313.62	44268.96
	FRAC_AM	1.56	1.74	1.85
	CIRCLE_AM	0.87	0.84	0.77
	CONTIG_AM	0.45	0.62	0.32
	PAFRAC	1.56	1.50	1.5802
Isolation\Proximity	*PROX_AM*	48.73	48.53	23.92
	ENN_AM	1.83	1.160	1.265
Contagion\Interspersion	*CLUMPY*	0.41	0.63	0.28
	PLADJ	54.12	70.02	40.69
	AI	54.63	70.33	41.14
	SPLIT	1456.65	4157.30	67779.88
	MESH	0.004	0.126	0.001
Connectivity	*COHESION*	88.03	93.742	77.87
	CONNECT	20.35	10.50	37.18

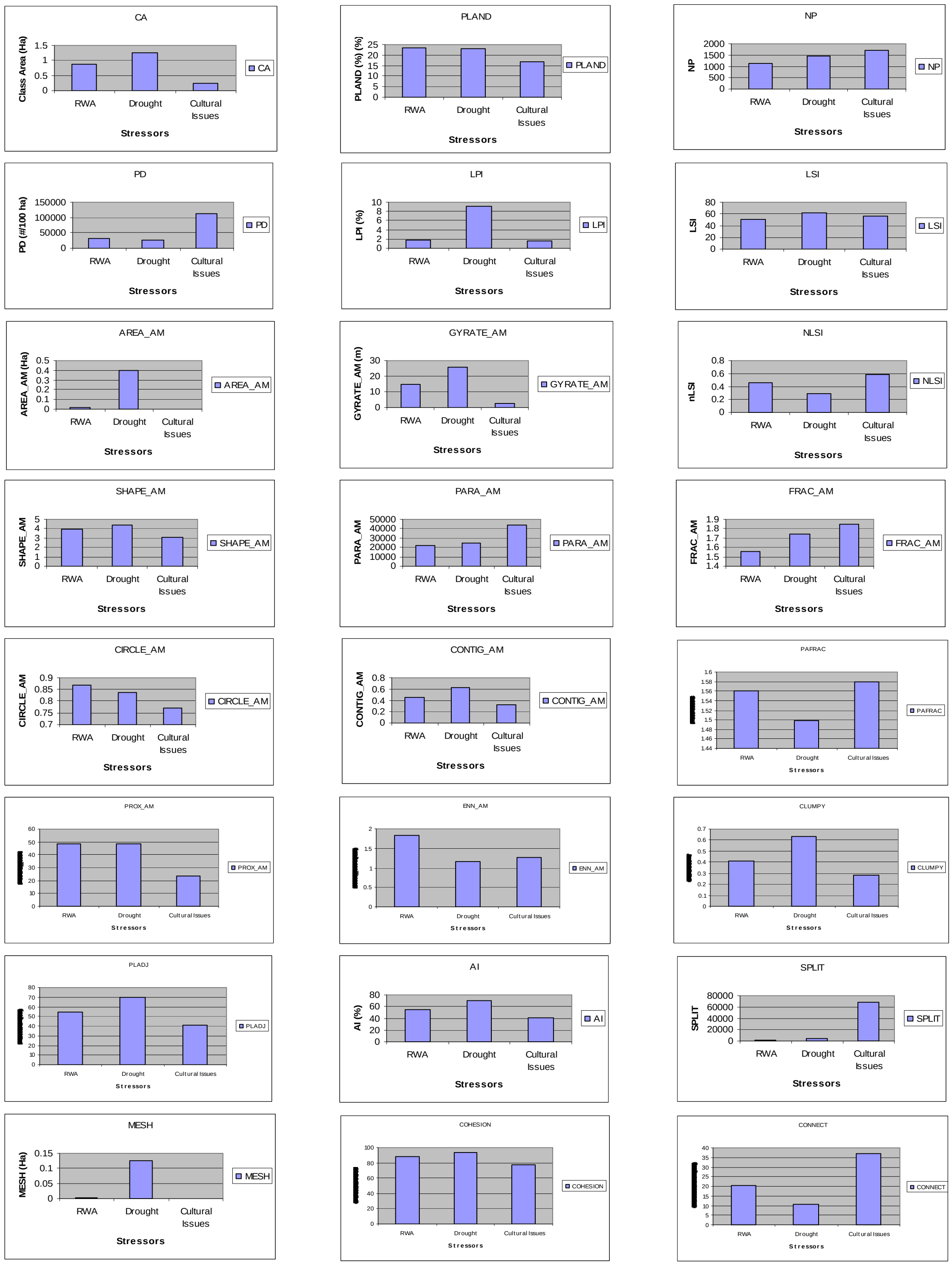

Figure 11 Graph of each Landscape metrics

Table 4. *T*-significance test for the three types of wheat plant damage. The cell contains the p-values for each landscape metrics. The comparison is among RWA and Drought, RWA and Cultural Issues, or Drought and Cultural Issues. Results significant at p<0.05 are in bold. 1: compares RWA to Drought, 2: compares RWA to Cultural Issues, and 3: compares Drought to Cultural Issues. The level of significance is 0.05. *s* indicates a relationship statistically significance, and *ns* a relationship not statistically significant

Patterns	Metrics	*T*-test pairwise comparison		
		RWA	Drought	Cultural Issues
Area\Density\Edge	CA	***P < 0.05***	ns	ns
	PLAND	ns	ns	ns
	NP	ns	ns	ns
	PD	ns	ns	ns
	LPI	ns	ns	ns
	LSI	ns	ns	ns
	AREA_AM	ns	ns	ns
	GYRATE_AM	ns	ns	ns
	nLSI	ns	***P < 0.05***	ns
Shape	SHAPE_AM	ns	ns	ns
	PARA_AM	ns	***P < 0.05***	ns
	FRAC_AM	ns	ns	ns
	CIRCLE_AM	ns	ns	ns
	CONTIG_AM	ns	ns	ns
	PAFRAC	ns	ns	ns
Isolation\Proximity	PROX_AM	ns	ns	***P < 0.05***
	ENN_AM	***P < 0.05***	ns	ns
Contagion\Interspersion	CLUMPY	ns	ns	ns
	PLADJ	ns	***P < 0.05***	ns
	AI	ns	***P < 0.05***	Ns
	SPLIT	ns	ns	Ns
	MESH	ns	ns	Ns
Connectivity	COHESION	***P < 0.05***	ns	Ns
	CONNECT	***P < 0.05***	ns	Ns

Discussion

The assumption in this study is that disruption of the integrity of large homogenous areas of healthy wheat plants was caused by RWA, Drought and Cultural Issues. The emphasis was to quantify landscape pattern induced by the three types of stress that affect the wheat fields. The quantification of spatial pattern of stress has always been an important issue when studying the pattern-process relationship (O'Neill et al., 1988, Turner and Gardner, 1991, and McGarigal and Marks, 1995).

Overall, nine landscape metrics exhibited statistical significant difference (Table 4). The quantification of spatial pattern of wheat fields was grouped in five types of landscape metric that include Area/Density/Edge metrics, Shape complexity metrics, Isolation/Proximity metrics, Contagion/Interspersion metrics, and the connectivity metrics. The Area/Density/Edge metrics measured the configuration of size, and edge of patches at the class level. The study revealed that two landscape metrics, CA and nLSI, were statistically significantly different. Class area (CA) measures (in ha) the composition of the wheat field, specifically how much of the wheat field consisted of a particular patch type. Patches of wheat infested by RWA were smaller than patches affected by drought.

Normalized Landscape shape index (nLSI) is a metric related to the edge of each patch in the same class and measures the aggregation or clumpiness of each class in the landscape. This index has no units of measurement and ranges from 0 to 1. The nLSI equals 0 when the landscape consists of a single square or maximally compact patch. When nLSI equals 1, the patch type becomes maximally disaggregated. Even though patches affected by Cultural Issues had greater nLSI that patches affected by RWA and

Drought, they were not significantly different (Table 4). Patches affected by RWA had more edges than patches affected by Drought.

The shape complexity metrics are related to the geometry of patches. One landscape metric only, PARA_AM, was significantly different when comparing stress induced by RWA from stress induced by Cultural Issues.

Isolation/Proximity metrics refer to the tendency of patches to be relatively separated (in distance) from other patches of the same or similar class (McGarigal et al., 2002). These metrics measure the relative isolation of patches. The Area-Weighted Mean Euclidean Nearest Neighbor Distance (ENN_AM) and the Area-Weighted Mean Proximity index (PROX_AM) are both landscape metrics that differed significantly among stresses. ENN_AM showed significant difference between stress induced by RWA with stress induced by Drought. No significant difference was found in comparing stress induced by RWA with stress induced by cultural issue and also when comparing stress induced by drought with cultural issues (Table 4). The Area-Weighted Mean of Euclidean nearest-neighbor (ENN_AM) measures the isolation of patches by measuring the geometric shortest distance between patches. The Patches infested by RWA have a ENN_AM greater than patches affected by Drought or Cultural Issues. In other words, patches infested by RWA are more isolated than patches infested by Drought or Cultural Issues. The Area-Weighted Mean Proximity (PROX_AM) index was developed by Gustafson and Parker (1992) and considers the size and proximity of all patches whose edges are within a specified search radius of the focal patch. In this study we considered the radius to be twice the size of each pixel. The PROX_AM showed a significance difference in comparing stress induced by Drought from stress induced by Cultural

Issues. No significant difference was noticed when comparing patches affected by RWA with patches affected by drought and cultural issues (Table 4). The PROX_AM is a positive number and does not have units of measurement. When PROX_AM is minimum, the patch has no neighbors of the same patch type within the specified search radius. This indicator increases as the neighborhood (defined by the specified search radius) is increasingly occupied by patches of the same type and as those patches become closer and contiguous (or less fragmented) in distribution.

Contagion/Interspersion metrics refer to the tendency of patches to be spatially aggregated, or to the intermixing of patches of different types, based on the adjacencies of patches on a class. These metrics measure landscape texture by examining the aggregation and intermixing of patches. I computed five Contagion/Interspersion metrics, but two only, Percentage of Like Adjacencies (PLADJ) and Aggregation Index (AI) showed a significant difference between stress induced by RWA from stress induced by Cultural issues (Table 4). Both metrics revealed that patches of RWA were less dispersed than patches of drought. The Percentage of Like Adjacencies (PLADJ) measures the degree of aggregation of the patches. This metric is also a measure of class-specific contagion. PLADJ ranges from 0 to 100. PLADJ is minimum when the patches are dispersed (or disaggregated), and it is maximum when patches are maximally contagious. Aggregation Index (AI) measures the percentage or frequency different pair wise patches are distributed. AI is a percentage and ranges from 0 to 100. AI equals 0 when patches are disaggregated, there are no like adjacencies. AI increases when patches are increasingly aggregated and tend to 100. In this case, patches are aggregated into single or compact patches. Table 3 shows that that patches of affected by drought were more contagiously dispersed and disaggregated that patches affected by RWA and Cultural issues.

The connectivity metric measures the functional connections among patches in a class. The Patch Cohesion Index (COHESION) and the Connectance Index (CONNECT) were statistically significant different when comparing stress induced by RWA from stress induced by Drought (Table 4). Patch cohesion index measures the physical connectedness of patch type. The connectedness is refer to the fact that two patches of the same type are adjacent and joined in space (Burel and Baudry, 1999). COHESION index does not have units, and ranges from 0 to 100. COHESION approaches 0 as the proportion of the landscape comprised of the focal class decreases and becomes increasingly subdivided and less physically connected. COHESION increases as the proportion of the landscape more connected. Patches infested by RWA are less connected than patches affected by Drought. CONNECT is the landscape metrics that measures the percentage of the number of functional joinings between all patches of the corresponding patch type. This index equals zero (0) when either the class consists of a single patch or none of the patches of the class are "connected". It equals 100 when every patch of the class is connected. There are significant difference in connectedness and connectivity between patches affected by RWA and patches affected by drought (Table 4). According to Table 3, patches affected by RWA had high connectedness and poor connectivity.

Conclusion

The present study was an opportunity to combine Remote Sensing technology, Geographic Information System techniques and spatial pattern analysis to explore the potential of multispectral data to detect, map, and quantify spatial pattern of RWA infestation on wheat fields. An array of landscape metrics were generated at the class level and provided information useful to analyze and understand the spatial pattern of RWA on wheat fields. No single landscape metric was able to characterize infestation by RWA. The study revealed that nine landscape metrics: CA, nLSI, PARA_AM, PROX_AM, ENN_AM, PLADJ, AI, COHESION and CONNECT were satistically significant in comparing stress induced by RWA with other stress causing factors. Using the combination of multispectral data and landscape metrics made it possible to distinguish RWA infested patches from stressed patches caused by other factors. The detection and quantification of wheat field stress may help in mapping RWA infestations and may also have implications for site-specific pesticide application and for monitoring systems for the RWA.

References

Anonymous. 2008. Hi-Tech Electronics: RGB (3-CCD), Color IR Camera-AreaSan/Line Scan camera. MS3100. http://www.hitech.com.sg/rl/multispectral/MS3100_Data_Page.htm visited 07/03/2008.

Adams, M.L., W. D Philpot, and W. A. Norvell. 1999. Yellowness index: An application of spectral second derivatives to estimate chlorosis of leaves in stressed vegetation. International Journal of Remote Sensing 20(18):3663-3675.

Archer, T. L., and E. D. Bynum Jr. 1992. Economic injury level for the Russian wheat aphid on dryland winter wheat. J. Econ. Entomol. 85: 987–992.

Basky, Z. 2003. Biotypic and pest status differences between Hungarian and South African population of Russian wheat aphid, Diuraphis noxia (Kurdjumov) Homoptera: Aphidae). Pest Management Science 59(10):1152-1158.

Burd, J. D., and G. W. Burton. 1992. Total chlorophyll fluorescence profiles of Russian wheat aphid resistant and suspectible wheat, pp101-108. In W. P. Morisson. Proceedings of the fifth Russian wheat aphid conference, 16-28 January 1992, Fort Worth, TX. Great Plains Agriculture Council Publications 142.

Burd, J. D., R. A. Butts, N. C. Elliott, and K. A. Shufran. 1998. Seasonal development, overwintering biology, and host plant of Russian wheat aphid (Homoptera:Aphididae) in North America, pp 65-99.

Burel, F., and J. Baudry. 1999. Landscape Ecology: concepts, methods, and application. Science Publishers, Inc. Enfield, NH

Clua, A., A. Vasicek, H. O. Chidichimo, A.F. G. Dixon, A. M. Castro, S. Ramos, and D. O. Gimines. 2004. The biological characteristics and distribution of the greenbug, Schizaphis graminum, and Russian wheat aphid, Diuraphis noxia (Hemiptera: Aphididae) in Argentina and Chile. European Journal of Entomology 10(1):193-198.

Dolatti, L., B. Ghareyazie, S. Moharranipour, and M. R. Noori-Daloii. 2005. Evidence for regional diversity and host adaptation in Iranian populations of Russian wheat aphid. Entomologia Experimentalis et Applicata 114(3):171-180.

Elliott, N. C., M. Mirik, Z. Yang, T. Dvirak, M. Rao, J. Michels, V. Catana, M. Phoofolo, K. Giles and T. Royer. 2005. Aircraft multi-spectral remote sensing for Russian wheat aphid infestations. 20th Biennal Workshop on Aerial Photography, Videography and High Resolution Digital Imagery for Resource Assessment. Oct 4-6, 2005. Weslaco, TX.

Frohn, R.C. 1997. Remote Sensing for Landscape Ecology, Lewis Publishers, Boca Raton.

Gustafson, E. J., and G. R. Parker. 1992. Relationships between landcover proportion and indices of landscape spatial pattern. Landscape Ecology 7(2):101–110.

Hatting, J. L., S. P. Wraight, and R. M. Miller. 2004. Efficacy of beauveria bassiana (Hyphomycetes) for control of Russian wheat aphid (Homoptera:Aphidae) on resistant wheat under field conditions. Biocontrol Science and Technology 14(5):459-473.

Lillesand, T.M., and R.W. Kiefer. 2000. Remote Sensing and Image Interpretation. 4th Edition. John Willey and Sons New York, NY.

McGarigal, K., S. A. Cushman, M. C. Neel, and E. Ene. 2002. FRAGSTATS: Spatial Pattern Analysis Program for Categorical Maps. www.umass.edu/landeco/research/fragstats/fragstats.html visited November 25, 2007

McGarigal, K., and B. J. Marks. 1995. FRAGSTATS: spatial pattern analysis program for quantifying landscape structure. USDA For. Serv. Gen. Tech. Rep. PNW-351.

Metternicht, G. 2003. Vegetation indices derived from high-resolution airborne videography for precision crop management. International Journal of Remote Sensing 24(14): 2855-2877.

Miller, H., D. R. Porter, J. B. Burd, D. W. Mornhinweg, and R. L. Burton. 1994. Physiology effects of Russian wheat aphid (Homoptera:Aphididae) on resistant and susceptible barley. Journal of Economic Entomology 87:493-499.

Mirik, M., G. J. Michels Jr, S. Kassymzhanova-Mirik, and N. C. Elliott. 2007. Reflectance characteristics of Russian wheat aphid (Hemiptera: Aphididae) stress and abundance in winter wheat. Computers and Electronics in Agriculture 57(2):123-134.

Morisson W. P., and F. B. Peairs. 1998. Response model concept and economic impact. Pages 1-11. *In* Quisenberry and F. B. Peairs, Editors Response model for an introduced pest- The Russian wheat aphid. Thomas Say Publications in Entomology. Lanham, MD.

O’Neil, R. V., J. R. Krummel, R. H. Garder. 1988. Índices of landscape pattern. Landscape Ecology 1:153-162.

Puterka, G.J, J.D. Burd, D. Porter, K. Shufran, C. Baker. 2007. Distribution and Diversity of Russian Wheat Aphid (Hemiptera: Aphididae) Biotypes in North America. Journal of Economic Entomology 100(5):1679–1684

Reviriego, M. E., L. R. Descamps, A. A. Ferreroy, and A. A. Suarez. 2004. Field efficacy and laboratory toxicity tests of insecticides against Diuraphis noxia (Homoptera : Aphididae). International Pest Control 46(5):260-262.

Riitters, K.H., R.V. O’Neill, C.T. Hunsaker, J.D. Wickham, D.H. Yankee, S.P. Timmins, K.B. Jones and B.L. Jackson. 1995. A factor analysis of landscape pattern and structure metrics. Landscape Ecology. 10:23–39.

Royer, T.A., K.L. Giles, S.D Kindler, and N. C. Elliott. 2001. Developmental response of three geographic isolates of Lysiphlebus testaceipes (Hymenoptera: Aphididae) to temperature. Environmental Entomology 30(4):637-641.

Stary, P. Z. Basky, L. K. Tanigoshi, and Z. Tomanovicc. 2003. Distribution and history of Russian wheat aphid, Diuraphis noxia (Kurdj.) in the Carpathian Basin (Hom., Aphididae).

Thomas, J., G. Hein, D. Baltensperger, L. Nelson, and S. Haley. 2002. Managing the Russian Wheat Aphid with resistant varieties. File NF307 under: Insect and Pests. C-5, Field Crops. Nebraska Cooperative Extension. University of Nebraska, Lincoln, NE.

Turner, M. G., and R. H. Gardner. 1991. Quantitative methods in landscape ecology. Springer-Verlag, New York.

Turner, M.G., R.H. Gardner, and R. V. O'Neill. 2001. Landscape ecology in theory and practice: Pattern and process. Springer-Verlag New York.

Webster, J.A., K. J. Starks, R. L. Burton. 1987. Plant resistance studies with Diuraphis noxia (Homoptera: Aphididae), a new United States wheat pest. Journal of Economic Entomology 80:944-949.

Webster, J., Treat, R., Morgan, L., and N. Elliott. 2000. Economic impacts of the Russian wheat aphid and greenbug in the western United States 1993–1994, 1994–1995, and 1997–1998. U.S. Department of Agriculture, ARS Service report PSWCRL Rep. 00-001

CHAPTER V

USING DISCRIMINANT FUNCTION ANALYSIS TO DIFFERENTIATE STRESS INDUCED BY RWA IN WHEAT FIELDS

Abstract

The Russian wheat aphid (RWA) *Diuraphis noxia* (Mordvilko) is a major pest of winter wheat and barley in the United States. RWA has affected the United States Great Plains region from Texas to the Rocky Mountains and Canada where loss to wheat producers attributed to RWA is estimated at over $1 billion. RWA induces stress to the wheat crop by damaging plant foliage, lowering the greenness of plants, and affecting productivity. Remote sensing is a very effective tool for detecting stressed and healthy wheat plants. Stress detected in wheat fields may be a mixture of several conditions which vary spatially across a field. Stress may result from several factors such as topography, nutrient deficiency, drought, diseases, pests, etc, that can impact individually or collectively. The present study investigated a method that can help to differentiate the stress induced by RWA from other stress causing factors. The study used a combination of several approaches, remote sensing, geographic information systems, and spatial pattern analysis, to prepare information that was applied in a discriminant analysis to differentiate stress induced by RWA infestation from other types of plant stress. The

study concluded that it is possible to discriminate stress induced by RWA from other stressor factors and map patches of stressed wheat using multispectral Images. Overall, 97.9 percent of original patches of stress were correctly categorized. Patches affected by RWA were 95.4 percent classify, patches affected by cultural issues, 99.1 percent and patches affected by drought were 99.00 percent correctly classified.

Introduction

The Russian wheat aphid (RWA) *Diuraphis noxia* (Mordvilko) is a major pest of winter wheat (*Triticum aestivum*) and barley (*Hordeum vulgare*) (Puterka et al., 2007; Vandenberg et al., 2001). It has spread northward in the Great Plains, from Texas, since it was identified in Muleshoe, TX in 1986 (Kindler et al., 1991; Jones et al., 1989; Morisson and Peairs, 1998; and Stoetzel, 1987). The Great Plains region has been affected from TX, to the Rocky Mountains, and Canada where loss to wheat producers attributed to RWA is estimated to total over $1 billion since 1986 (ARS, 2003).

The RWA is a sap-sucking pest that invades wheat fields from emergence to harvest. It feeds at the base of young wheat leaves causing symptoms that include longitudinal chlorotic streaking and leaf rolling (Webster et al., 1987). Thus, the RWA infestation induces stress to wheat crop by damaging the plant foliage, lowering the greenness of plants, and affecting the wheat crop productivity. RWA infestations in wheat fields are unpredictable in time and space (Elliott et al., 2005).

Remote sensing can be used to distinguish damage caused by RWA and quantify its abundance (Mirik et al., 2007). The technique measures the reflectance of light from leaves and can be very effective in detecting stressed and healthy wheat plants. Stress detected in wheat fields may be a mixture of several conditions which vary spatially across a field. Stress may result from several factors such as topography, nutrient deficiency, drought, diseases, pests, etc, that can impact individually or collectively.

The geographic information system (GIS) is a tool that can manage spatial data and create and analyze maps (Fadaie et al., 2001; Guienko and Doytsher, 2003; Lo Seen, 2003). The field of landscape ecology provides spatial pattern indices that can characterize patches within a landscape. A wheat field is composed of patches of stressed and healthy wheat, and information that it contains can be used to differentiate stress induced by RWA from other stresses.

Discriminant analysis is one of several statistical procedures to examine differences between two or more groups of objects with respect to several variables (Klecka, 1980). This powerful technique has been used in research in fields such as education, medicine, psychology, sociology, political science, and ecology. For example, medical researchers might record different variables that relate to a patient's background in order to learn which variable or set of variables best explains or predicts whether a patient is likely to recover completely, partially or not at all.

In agricultural research, Piron et al. (2008) used a quadratic discriminant analysis to select the best combination of wavelength bands to detect various weed species located within carrot rows, and discriminate weeds from crops. The best combination included three wavelength bands centered at 450, 550 and 700 nm, with an overall classification accuracy of 72 percent. Lopez-Granados et al. (2008) conducted field studies of the potential of multispectral classification of late-season grass weeds in wheat. They applied discriminant analysis and other classification techniques. Fisher's linear discriminant analysis, feedforward neural networks and one-layer neural networks showed classification percentages that were between 90 and 100 percent. They concluded that mapping grass weed patches in wheat was feasible with analysis of real-time and high-resolution satellite imagery.

This is the final study I conducted on RWA. The first study explored the relationship between RWA and topographic and edaphic factors. The second explored the potential to use multispectral imagery data and a spatial quantification approach to identify and characterize stress, mainly induced by RWA infestation. In this study, the objective is to investigate a method that can help to differentiate the stress induced by RWA from other stress causing factors. A combination of techniques was used to prepare information generated in the first two studies for application of discriminant analysis to differentiate RWA infestation from other types of plant stress.

Materials and Methods

The procedure in this study was to create layers of information that were exported to a spreadsheet for statistical analysis. Figure 1 is the flow chart of the spatial analysis and displays the overall procedure. Data used for the analysis were topographic data, soil texture, and landscape metrics. ArcView software, version 3.3 (Environmental System Research Institute 2002) was used for GIS operations. FRAGSTATS 3.0 (McGarical and Marks, 1995) was used to generate landscape metrics. Statistical analyses were performed using SPSS version 16 (SPSS Inc., 2007)

Study area

The study site is located around Boise City at 36º.73’ N, -102º.51’ W, in Cimarron County in the panhandle of Oklahoma. Boise city is surrounded by several hectares of agricultural lands where mainly wheat is planted in September – October, and harvested in June – July, each season. The area has an annual average precipitation of 470.6 millimeters, and an annual mean temperature of 13.05º Celsius. June is the wettest month of the year with an average of 72.2 millimeters.

Data Generation and analysis

The data used in this study were landscape metrics, soil data and topographic data. Landscape metrics were computed using FRAGSTATS from classified multi-spectral images collected in April - May 2005, and 2007. The Multi-spectral image data for each selected wheat field were acquired using a Duncan Tech camera, model MS3100-CIR, mounted NADIR in the fuselage of a Cessna 172 aircraft. The camera is a 3-CCD (Charge Coupled Device) that has three channels: near infrared, red and green (Channel1, Channel 2 and Channel 3), centered at 800, 650, and 550 nanometers with bandwidths of 65, 40, and 40 nanometers (Anonymous, 2008). The combination of the three channels was used in the image processing.

Topographic data were Aspect, Relative Elevation, and Slope derived from USGS 10-meter Digital Elevation Model (DEM) data using the Surface Menu procedure in ArcView. DEM data were downloaded from the USGS website for each selected wheat field.

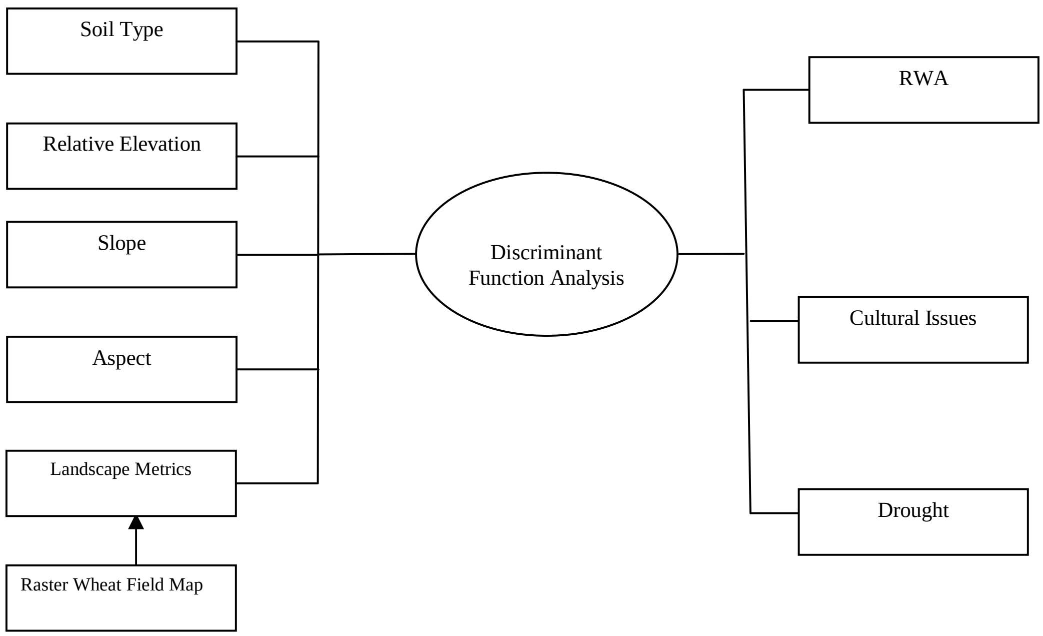

Figure 1. Flow chart of spatial analysis

Aspect was derived from DEM data. Aspect is an angular measure in degree from 0 to 360 degrees. It represents the position or direction of the slope face relative to North. The Relative Elevation was calculated by transforming Elevation from DEM data. Relative elevation reflects the difference in elevation within each field whereas Elevation primarily reflects the difference in elevation among wheat fields. The Relative Elevation was computed using the following equation:

$$\text{Relative Elevation} = (X_i - \bar{X})/\bar{X}$$

Where X_i is the elevation at each point within the wheat field derived from the DEM data, and $\bar{X}$ is the mean elevation of the field. Slope is another variable that was derived from DEM data. Slope can be measured in degrees or in percent slope. Percent slope was used in this study, which is a percentage of change in elevation over distance.

Soil data were acquired from the Soil Survey Geographic (SSURGO) database housed by the Natural Resources Conservation Service (NRCS). The SURGO database contains physical and chemical soil properties for several soil series identified in the United States. Soil shape files and soil names were downloaded from the NRCS website to build the soil layer of each selected wheat field. Soil information was first grouped by soil name, then by texture according to the soil triangle for each soil texture. Soil texture was characterized by the percentage of Clay, Silt and Sand contained in each soil.

FRAGSTATS was used to quantify spatial pattern metrics. FRAGSTATS program is available online. It generates an array of metrics at patch, class, and landscape levels. This study focused on spatial pattern metrics quantified at the patch level, and 30 landscape-class metrics were generated for the analysis.

Data generated were displayed as map layers in ArcView. Map layers comprised Aspect, Relative Elevation, Slope, and percentage of Clay, Silt and Sand. Xtools, an ArcView extension, was used to clip and intersect themes. Attributes were exported in tabular format as data in Microsoft Excel.

In total, 35 predictor variables were generated and exported to the SPSS software for the statistical analysis. These variables included 30 landscape metrics, 3 topographic variables, and 2 soil variables. Table 1 describes each variable used in the analysis. Due to high correlation among the three soil variables, percent of silt was not included in the analysis. The study assumed that predictor variables were normally distributed, the groups were homogeneous and unequal sample sizes were acceptable. A stepwise discriminant function analysis (DFA) was performed using SPSS. The objective was to find a set of variables that best discriminated patches of wheat plants infested by RWA from stressed patches resulting from other stress factors. A random selection of 70 percent of available patches was used to create the discriminant model. The remaining patches were used to validate the model.

Table 1. Variables used in the analysis. The table describes landscape metrics, topographic and edaphic variables.

	Variables	***Abreviations***	***Description***
Landscape metrics	Patch area	Area	Area of each patch, important and useful information contained in class and landscape
	Standard deviation of patch area at class	Area_csd	The standard deviation of patch area at class level
	Standard deviation of patch area at landscape	Area_lsd	The standard deviation of patch area at landscape level
	Patch perimeter	Perim	Total distance around each patch
	Standard deviation of perimeter at class	Perim_csd	The standard deviation of perimeter at class level
	Standard deviation of perimeter at landscape	Perim_lsd	The standardized deviation of perimeter at landscape level
	Radius of Gyration	Gyrate	The measure of the measure of class extent, involves the mean distance (m) between each cell in the patch and the patch centroid.
	Standard deviation of patch area at class	Gyrate_csd	The standard deviation of gyrate at class level
	Standard deviation of patch area at landscape	Gyrate_lsd	The standard deviation of gyrate at landscape level
	Perimeter-Area Ratio	Para	The ratio of patch perimeter to area measuring shape complexity across the landscape
	Standard deviation of para at class	Para_csd	The standard deviation of perimeter-ration at class level
	Standard deviation para at landscape	Para_lsd	The standard deviation of perimeter-ratio at landscape level
	Shape Index	Shape	The ratio of patch perimeter to the minimum perimeter for the maximally compact patch of the same patch area across the class
	Standard deviation shape index at class	Shape_csd	The standard deviation of shape index at class level
	Standard deviation of shape index at landscape	Shape_lsd	The standard deviation of shape index at landscape level
	Fractal Dimension Index	Frac	The ratio across the landscape of the 2 times logarithm of patch perimeter to logarithm of patch area, that measures shape complexity across a range of spatial scales.
	Standard deviation of Fractal dimension index at class	Frac_csd	The standard deviation of fractal dimension index at class level
	Standard deviation of Fractal dimension index at landscape	Frac_lsd	The standard deviation of fractal dimension index at landscape level
	Related Circumscribing Circle	Circle	The measure of the linearity or elongation of patches. 0=CIRCLE<1
	Standard deviation Circle at class	Circle_csd	The standard deviation of circle index at class level
	Standard deviation of Circle at landscape	Circle_lsd	The standard deviation of circle index at landscape level
	Contiguity Index	Contig	The measure of the spatial connectedness, or contiguity, of cells within a grid-cell patch to provide an index of patch boundary configuration and thus patch shape
	Standard deviation of Contiguity Index at class	Contig_csd	The standard deviation of contiguity index at class level
	Standard deviation of Contiguity Index at landsacape	Contig_lsd	The standard deviation of contiguity index at landscape level
	Proximity Index	Prox	The ratio of the sum of patch areas to the nearest edge-to-edge distance squared between patches in a specific radius
	Standard deviation of proximity index at class	Prox_csd	The standard deviation of proximity index at class level
	Standard deviation of proximity at landscape	Prox_lsd	The standard deviation of proximity index at landscape level
	Euclidean Nearest Neighbor Distance	Enn	The measure of the shortest straight-line distance between the focal patch and its nearest neighbor of the same class
	Standard deviation of ENN at class	Enn_csd	The standard deviation of ENN index at class level
	Standard deviation of ENN at landscape	Enn_lsd	The standard deviation of ENN index at landscape level
Topographic variables	Aspect	Aspect	The angular measure in degree from 0 to 360
	Relative Elevation	ReElevation	The difference in elevation within each field
	Slope	Slope	The change in elevation over a distance.
Edaphic variables	Percentage of clay	Clay	The percent of clay in soil
	Percentage of sand	Sand	The percent of sand in soil

Results and Discussion

A stepwise discriminant function analysis was done with 35 predictor variables using the Wilks' Lambda method, to assess how well stress induced by RWA could be separated from the other two general categories of damage we observed referred to here as Cultural Issues and Drought. A total of 4928 patches were used in the analysis (Table 2). Out of this total, 3495 patches (70.9 percent) were used to build the model and 1433 (29.1 percent) were used to validate the model. The three types of stress that were compared were: Group 1 (N =1111), stress or damage induced by RWA; Group 2 (N = 1125), stress or damage induced by Cultural Issues; and Group 3 (N = 1259), stress or damage induced by Drought. All variables were tested for their equality among categories of stresses. They were significantly different among categories except one variable, the Relative Elevation ($p=0.764$), that had a *p-value* greater than *0.05*. Therefore, relative elevation was dropped as predictor variable.

A pooled within-groups correlation matrix was calculated to assess whether there was mutlicollinearity among variables. A correlation that exceeded 0.7 in absolute value was considered very highly correlated. The results show that most of the variables were strongly intercorrelated with other predictor variables, and had high multicollinearity except for the Fractal, Proximity, and Euclidean Network metrics.

Table 2. Summary of patches used in the analysis. Out of 4928 patches, 3495 were used to generate the model and 1433 were used for the validation.

Patch	*Number*	*Percent*
Used for the model	3495	70.9
Used for validation	1433	29.1
Total	4928	100.0

Table 3. Eigenvalues per discriminant function. Two functions were generated. The table summurizes the eigenvalue, percent of variance, and the canonical correlation.

Function	*Eigenvalue*	*% of Variance*	*Cumulative %*	*Canonical Correlation*
1	9.421	64.1	64.1	0.951
2	5.275	35.9	100.0	0.917

Table 4. Wilks' Lambda value per discriminant function. The Wilks'lambda test whether there are differences among the means of the three types of stress.

Test of Function	*Wilks' Lamdba*	*Chi-Square*	*Df*	*Sig.*
1 through 2	0.015	14553.65	44	0.00
2	0.159	6393.79	21	0.00

Table 5. Standardized discriminant function analysis. The table illustrates the coefficient of 21 variables to discriminate stress. Two functions were generated. Function 1 discriminated the group of patches damaged by RWA from Drought and Cultural Issues, and the Function 2 discriminated patches of wheat damaged by Drought from the ones damaged by RWA and Cultural Issues.

Variables	***Function 1***	***Function 2***
Area	164.115	44.367
Area_csd	0.471	0.320
Perim	-0.016	-.005
Gyrate	-0.097	-.113
Gyrate_csd	-0.323	0.258
Para_csd	-1.693	-0.792
Shape	3.021	2.145
Shape_csd	-1.876	-1.822
Frac	0.121	0.364
Frac_csd	-0.203	-0.775
Circle	-14.147	7.624
Circle_csd	2.428	-1.306
Contig	-0.093	3.614
Prox	0.002	-0.002
Prox_csd	-0.280	0.110
Enn	-0.001	0.132
Enn_csd	-0.064	-0.020
Aspect	-0.002	0.000
Slope	0.178	0.163
Clay	0.378	-0.083
Sand	0.124	0.053
(Constant)	-16.676	-14.305

The stepwise discriminant function method retained 21 out of 35 variables initially selected (Table 3). All 21 predictor variables were statistically significant based on Wilks' Lambda. Two discriminant functions were created because there were three (3) groups of stress or damage. Table 3 displays the eigenvalue, percent of the variance explained, and the canonical correlation of each discriminant function. The first discriminant function explained 64.1 percent of variation among the three types of stress and the second function explained 35.9 percent. The discriminant functions had a canonical correlation of 0.951 and 0.917, respectively that were highly related to each group membership. Table 5 presents the value of each function and their statistical significance. The Chi-Square statistic for both discriminant functions was statistically significant χ^2= 14553.65, p = 0.00 and χ^2 = 6393.79, p = 0.00. The first discriminant function had a Wilk's Lamba that was smaller than the Wilks' Lambda of the second Discriminant function. The first discriminant function discriminated Group1 (RWA) from Group2 (Cultural Issues) and Group3 (Drought) combined. The second discriminant function discriminated Group2 (Cultural Issues) from Group 3 (Drought). The coefficients of the second Discriminant function were not interpreted.

Table 3 displays the coefficient of both discriminant functions for each variable in the analysis. The following variables Shape (2.768), Circle_CSD (2.291), Para (1.734), Clay (1.535), Sand (1.14), Area (0.976), Area_CSD (0.448), Frac (0.262), Prox (0.232), and Slope (0.102), contributed positively to discrimination between Group 1 (RWA), Group 2 (Cultural Issues) and Group 3 (Drought) in the first discriminant function. Other variables did not contribute, or contributed weakly, or negatively.

According to the Wilks' Lambda method, both discriminant functions are significantly different, meaning that the three types of groups of stress differ (Table 4). The smaller the Lambda, the more variables contributes to discriminant function. The value of Lambda varies from 0 to 1, with 0 meaning that group means differ, and the value 1 means that all groups are the same. Discriminant functions are the most powerful discriminators and are very informative and sufficient (Klecka 1980). Plotting discriminant function 1 against discriminant function 2 generated the graphic of classification of Group 1, 2 and 3 that displayed the location of centroids and data values (patches) of each group (Figure 2). The examination of the plot shows that the three types of stress are fairly distinct. The centroids are well separated and there are noticeable overlaps of the individual patches. These overlaps among groups represent confusion of patches that were mistakenly classified. Patches of affected by RWA (Group 1) overlap with patches of Drought (Group 3) and with some patches of Cultural Issues (Group 2). Patches caused by cultural issues were sometimes classified as membership of group 1 (RWA) or group 3 (Drought).

Three Fisher's linear discriminant functions were generated to classify stress in the wheat field. They are displayed in Table 6. From Table 7 it is evident that the discriminant function did a very good job in classifying patches affected by cultural issues and drought. Patches affected by RWA had more confusing classification. Some of the RWA patches were wrongly classified as member of the two other categories drought (4.6 percent) or cultural issues (0.3 percent). Table 7 shows that 95.4 percent of patches caused by RWA were correctly categorized, and 0.3 percent were wrongly

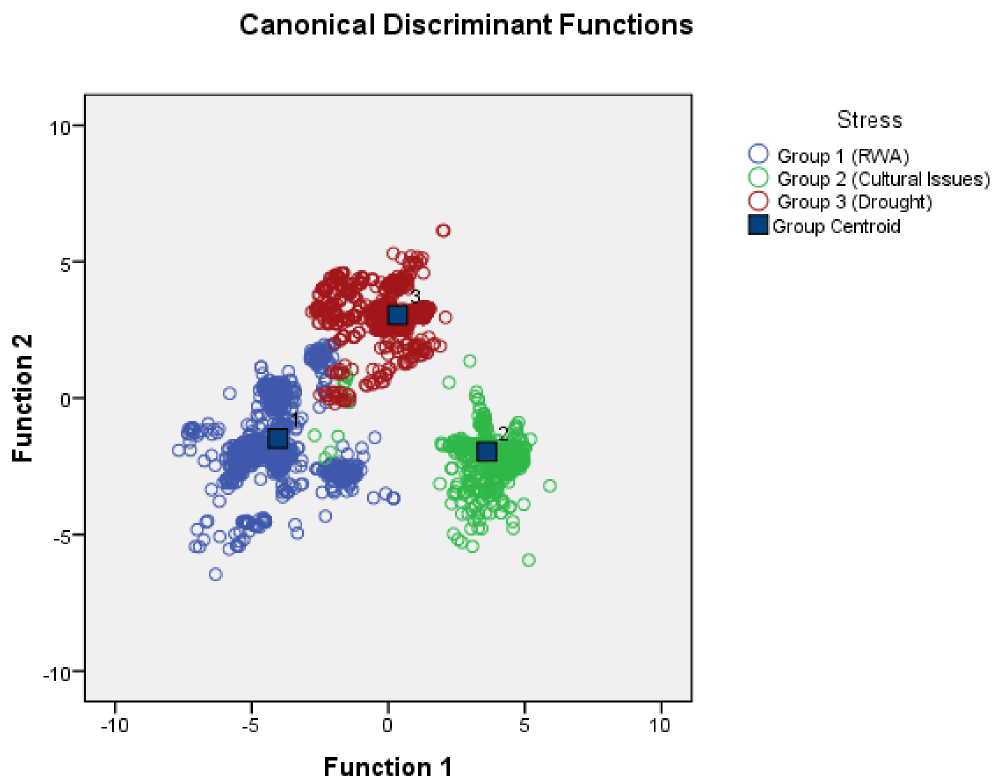

Figure 2. Plot of Discriminant functions. The graph is a space representation of the discrimination where Function 1 is plotted to Function 2

Table 6. Fisher’s linear discriminant functions for the three types of stress that affected wheat fields. The table represents the classification score for each patch and each stress. It illustrates three equations that determine to which type of stress a patch most likely belongs.

	Stress		
Variables	*RWA*	*Drought*	*Cultural Issues*
Area	3256.175	4489.310	4176.175
Area_csd	-7.607	-4.164	-4.095
Perim	-.065	-.184	-0.160
Gyrate	-5.269	-5.953	-6.202
Gyrate_csd	14.163	11.568	13.913
Para	0.003	0.004	0.004
Para_csd	-40.202	-52.763	-51.204
Shape	46.207	68.269	69.152
Shape_csd	-35.729	-49.187	-52.190
Frac	6.317	7.068	8.493
Frac_csd	-14.357	-15.537	-18.754
Circle	240.340	128.515	212.804
Circle_csd	-42.427	-23.237	-37.691
Contig	30.913	28.461	46.851
Prox	-0.021	-0.007	-0.022
Prox_csd	0.437	-1.755	-0.291
Enn	10.638	10.566	11.231
Enn_csd	-4.796	-5.276	-5.168
Aspect	-0.058	-0.071	-0.065
Slope	5.943	7.224	7.462
Clay	6.360	9.291	7.643
Sand	2.759	3.680	3.540
(Constant)	-311.647	-431.383	-444.893

classified as affected by Cultural Issues, and 4.6 percent were wrongly categorized as patches affected by Drought.

Patches affected by cultural issues were correctly classified at 99.0 percent. Less of 1 percent of patches was wrongly classified as patches affected by RWA or Drought. None of the patches of wheat categorized as affected by Drought were wrongly classified as affected by Cultural Issues. Only one percent of patches affected by Drought were mistaken as caused by RWA. Overall, 97.9 percent of the selected original groups of stress or damage were correctly classified.

To validate the model, 29 percent of cases or patches were excluded in the analysis, and used to create the discriminant function. Table 7 shows an overall of 98 percent of the originally unselected patches were correctly classified. The confusion of classification was slightly higher for patches classified as RWA than for the two other stresses, which had 99.4 percent of patches correctly classified as Cultural Issues and 98.6 percent as Drought. Less than 0.2 percent of patches caused by RWA were misclassified as Cultural Issues, and 3.9 percent were mistaken as Drought.

The study addresses the problem of whether landscape metrics, environmental variables, and soil texture could be used to discriminate stress induced by RWA from other stress causing factors. The combination of 35 variables in a stepwise discriminant function analysis revealed that 21 variables could be used to separate types of stress that affected wheat fields. The discriminant function in this study was a linear combination of the 21 variables that best separated the three types of stresses found in wheat fields. The model did well at predicting membership of patches of each of the three types of stress. Less than one percent of RWA patches were classified as impacted by Cultural Issues,

Table 7. Classification results for selected and not selected patches. The table reports how well patches were classified. Patches not selected were used to validate the model.

		Stress	*Predicted Group Membership*			
			RWA	*Cultural Issues*	*Drought*	*Total*
Patches selected	Count	RWA	1060	3	48	1111
		Cultural Issues	6	1115	4	1125
		Drought	12	0	1247	1259
	%	RWA	95.4	0.3	4.3	100.0
		Cultural Issues	0.5	99.1	0.4	100.0
		Drought	1.0	0.0	99.0	100.0
Patches not selected	Count	RWA	437	1	18	456
		Cultural Issues	2	484	1	487
		Drought	7	0.0	483	490
	%	RWA	95.8	0.2	3.9	100.0
		Cultural Issues	0.4	99.4	0.2	100.0
		Drought	1.4	0.0	98.6	100.0

while four percent were classified as affected by Drought. Validation of the model revealed comparable misclassification percentages.

The results of this study suggested that potential exists to separate patches of wheat infested by RWA from patches caused by other stress factors on the basis of landscape metrics and topographic and edaphic variables. However, the results need to be considered in context. Multispectral images used in this study were snapshots of wheat fields at a phenologically advanced stage of wheat growth. The pattern of RWA infestation could be different if snapshots were taken at earlier stages of plant development. Multispectral imagery used in this study lack the sensitivity to detect the RWA or to detect changes that may occur at the scale of individual wheat plants. Thus, patches of wheat plants were considered and compared to each other to assess the difference among the types of damage typically found in the wheat fields. The study indicates that it is possible to discriminate stress induced by RWA from other stress causing factors and map patches of stressed wheat using multispectral Images. Further studies are required to determine the potential of change of spatial pattern of RWA over time, and to assess specific landscape metrics and other environmental variables that might differentiate RWA stress from other types of stress if differences occur at other stages of wheat plants maturity.

References

Annonymous. 2008. Hi-Tech Electronics: RGB (3-CCD), Color IR Camera-AreaSan/Line Scan camera. MS3100. http://www.hitech.com.sg/rl/multispectral/MS3100_Data_Page.htm visited 07/03/2008

ARS. 2003. Annual Project Reports. http://www.ars.usda.gov/research/projects/projects.htm?ACCN_NO=407314&showpars=true&fy=2003 visited October 25, 2005.

Elliott, N. C., M. Mirik, Z. Yang, T. Dvirak, M. Rao, J. Michels, V. Catana, M. Phoofolo, K. Giles and T. Royer. 2005. Aircraft multi-spectral remote sensing for Russian wheat aphid infestations. 20th Biennal Workshop on Aerial Photography, Videography and High Resolution Digital Imagery for Resource Assessment. Oct 4-6, 2005. Weslaco, TX.

Fadaie, K., S. D. Slade, and I. de Rijcke. 2001. Geospatial information as a tool in legal dispute resolution. Geomatica 55(1): 79-90.

Guienko, G., and Y. Doytsher. 2003. Geographic information system data for supporting feature extraction from high-resolution aerial and satellite images. Journal of Surveying Engineering 129(4):158-164.

Jones, J. W., J. R. Byers, R. A. Butts, and J. L. Harris. 1989. A new pest in Canada: Russian wheat aphid, *Diuraphis noxia* (Mordvilko) (Homoptera:Aphididae). Canadian Entomologist 121:623-624.

Kindler, S. D., J. P. Breen, and T. L. Springer. 1991. Reproduction and damage by Russian wheat aphid (Homoptera:Aphididae) as influenced by fungal endophytes and cool-season turfgrasses. Journal of Economy Entomology 84:685-692.

Klecka, W. R. 1980. Discriminant analysis. Series: Quantitative application in social sciences. Sage Publications. The International Professional Publishers Newbery Park London, New Delhi.

Lo Seen, D. 2003. Geographical information system and remote sensing for monitoring the environment. Tropical Ecology 44(1):113-119.

Lopez-Granados, F., J.M. Pena-Barragan, M. Jurado-Exposito, M. Francisco-Fernandez, R. Cao, A. Alonso-Betanzos, and O. Fontenla-Romero. 2008. Multispectral classification of grass weeds and wheat (Triticum durum) using linear and nonparametric functional discriminant analysis and neural networks. Weed Research 48(1):28-37.

McGarigal, K., and B. J. Marks. 1995. FRAGSTATS: spatial pattern analysis program for quantifying landscape structure. USDA For. Serv. Gen. Tech. Rep. PNW-351.

Mirik, M., Jr. G.J Michels, S. Kassymzhanova-Mirik, N. C. Elliott, 2007. Reflectance characteristics of Russian wheat aphid (Hemiptera: Aphididae) stress and abundance in winter wheat. Computers and Electronics in Agriculture 57 (2): 123-134.

Morisson W. P., and F. B. Peairs. 1998. Response model concept and economic impact. Pages 1-11. *In* Quisenberry and F. B. Peairs, Editors Response model for an introduced pest- The Russian wheat aphid. Thomas Say Publications in Entomology. Lanham, MD.

Piron, A., V, Leemans, O. Kleynen, F. Lebeau, and M.E. Destain. 2008. Selection of the most efficient wavelength bands for discriminating weeds from crop. Computers and Electronics in Agriculture 62(2):141-148.

Puterka, G.J, J.D. Burd, D. Porter, K. Shufran, C. Baker. 2007. Distribution and Diversity of Russian Wheat Aphid (Hemiptera: Aphididae) Biotypes in North America. Journal of Economic Entomology 100(5):1679–1684.

Stoetzel, M. B. 1987. Information on and identification of *Diuraphis noxia* (Homoptera: aphididae) and other aphid species colonizing leaves of wheat and barley in the United States. Journal of Economic Entomology 80:694–704.

Vandenberg,J. D., L. E. Sandvol, S. T. Jaronski, M. A. Jackson, E. J. Souza, and S. E. Halbert. 2001. Efficacy of fungi for control of Russian wheat aphid (Homoptera : Aphididae) in irrigated wheat. Southwestern Entomologist 26(1):73-85.

Webster, J.A., K. J. Starks, R. L. Burton. 1987. Plant resistance studies with Diuraphis noxia (Homoptera: Aphididae), a new United States wheat pest. Journal of Economic Entomology.80:944-949.

CHAPTER VI

CONCLUSION

The present chapter concludes the study on assessing infestations of RWA within wheat fields using remote sensing. This study contributes to the RWA saga that started when the RWA was first detected in the United States in 1986. The study is part of an ongoing effort by many researchers to find techniques to mitigate the economic impact of the RWA. The relationship of RWA to edaphic and topographic factors was first explored, and then the potential of multispectral imagery was analyzed as a tool to rapidly identify and quantify the spatial pattern of stress within wheat fields. It was possible to differentiate stress induced by RWA infestation from other stress causing factors by combining edaphic and topographic data with data describing spatial characteristics of stressed patches.

This study supports the hypothesis that the population density of RWA is related to environmental conditions within wheat fields. Understanding the relationship between RWA population and environmental conditions helped explain the spatial pattern of RWA infestation within wheat fields. Stress induced by RWA was differentiable from stress induced by other stressors based on spatial pattern analysis of stressed patches within a field. The spatial pattern information was used along with edaphic and topographic information to differentiate RWA infestations. RWA infestations were reliably distinguished from patterns caused by other stress causing factors. Slope and percent sand were predictors that were interrelated with RWA population density. Both variables helped explain the variation of RWA population density within fields. Other topographic and edaphic variables such as aspect, relative elevation, and clay did not demonstrate predictive ability.

I showed that stress induced by RWA has a specific spatial pattern that can be identified, quantified, and mapped by using multispectral image data. The combination of remote sensing technology, Geographic Information Systems and the spatial pattern recognition techniques helped in exploring the potential of multispectral data to quantify and map the spatial pattern of stress within wheat fields. A set of landscape metrics generated from multispectral data has provided useful information to analyze and understand the spatial pattern of RWA infestation on wheat fields. This combination of multispectral data and landscape metrics combined with topographic and edaphic variables made it possible to differentiate RWA infested patches from stressed patches caused by other factors. The detection and quantification of patches of stress in wheat fields can help in mapping RWA infestations, and also have implications for site-specific pesticide application and for monitoring systems for the RWA.

Previous studies (e.g. Mirik et al., 2006; Mirik et al., 2006; and Yang et al., 2005) tested the feasibility of using unique spectral properties of RWA stressed wheat plants to differentiate stress caused by the RWA from that caused by other common stress factors. However, this approach does not work consistently on RWA. In this study RWA induced stress and that caused by other factors were distinguishable based on spatial properties. In fact, the previous studies on a closely related aphid (the greenbug) suggested that spectral reflectance is unlikely to exhibit differences among stress causing factors that are sufficiently large and consistent to be capable of differentiating among them (Yang et al., 2005; Mirik et al., 2006).

I relied on the spatial pattern information drawn from the multispectral image data to supplement spectral information to distinguish stress caused by RWA infestation from that caused by other factors. Plant damage often occurs in irregular patterns and varies within a field due to soil texture, topography, wind patterns and the randomness of infestation intensity. The study compared different stresses at the patch level. All metrics at individual patch level were combined in a discriminant analysis to differentiate patches affected by RWA from those affected by other factors. Further studies may consider using landscape metrics at the class and/or landscape level to compare and differentiate stress for entire wheat fields to differentiate heavily infested fields from those affected by other factors. These studies may permit stress to evaluated at the field scale and possibly to evaluate the need to take control measures.

Limitations of this study can be linked to landscape metrics. There is a proliferation of metrics that characterize landscape structure. The challenge is to determine the best set of metrics to include in the analysis and which metrics characterize the affect of stress induced by RWA on wheat fields. Another challenge includes metrics that can be linked to the economic threshold of RWA infestation. The economic threshold in this case results from an increase of the RWA population density that causes economic injury, defined as the population density where the cost of the lost grain equals the cost of management action (usually insecticide application). Further studies may require multiple sampling over the growing season to allow the differentiation of stress causing factors at field level and to relate the analysis of landscape metrics to the economic injury level.

Further studies of spatial pattern recognition of RWA infestation should explore other abiotic factors such as soil nutrients, organic matter, soil temperature, soil relative humidity, and plot size as potential predictors of RWA population density within fields. Topographic information should be collected at the sampling point and factors such as relative elevation, slope, and aspect should be derived from data collected at each sampling point in order to minimize positional error. Monitoring for RWA infestation should involve acquiring multispectral imagery biweekly from February or March to May, June or July depending on the geographic location. This monitoring might allow researchers to follow the progressive development of RWA infestations and explore landscape metrics behavior during the phenological development of wheat; and possibly to characterize the economic threshold which is dependent on RWA infestation level based on multispectral remote sensing.

References

Mirik, M., Jr. G.J Michels, S. Kassymzhanova-Mirik, N. C. Elliott, 2007. Reflectance characteristics of Russian wheat aphid (Hemiptera: Aphididae) stress and abundance in winter wheat. Computers and Electronics in Agriculture 57 (2): 123-134.

Mirik. M. G., J. Michels Jr., S. Kassymzhanova-Mirik, N. C. Elliott, V. Catana, D. B. Jones, R. Bowling. 2006. Using digital image analysis and spectral reflectance data to quantify damage by greenbug (Hemitera: Aphididae) in winter wheat. Computers and Electronics in Agriculture 51:86-98.

Yang, Z. 2005. Detection of greenbug infestation on wheat using ground-base radiometry. Doctorate Thesis. Oklahoma State University. Stillwater, OK.

VITA

Georges Ferdinand Backoulou

Candidate for the Degree of Doctor of Philosophy

DISSERTATION: USING MULTI-SPECTRAL IMAGERY TO DETECT AND MAP STRESS INDUCED BY RUSSIAN WHEAT APHID

MAJOR FIELD: Environmental Science

EDUCATION:

Doctor of Philosophy, Environmental Science, December 2008
Oklahoma State University, Stillwater, OK
Master of Science, Forest Resources, December 1998
Oklahoma State University, Stillwater, OK
Rural Development Engineer Diploma, May 1986
University Marien Ngouabi, Brazzaville, Republic of Congo

RELEVANT EXPERIENCE:

Graduate Research Assistant August 2003 – Present
Oklahoma State University, Department of Geography, Stillwater, OK
Advanced Technical Support 2000 – 2007
Creative Labs Stillwater, OK
Teaching Assistant 1999 – 2000
Oklahoma State University, Department of Geography, Stillwater, OK
Research Associate and Head of Forest Research Station 1991- 1995
Centre National de Recherches Forestières, Pointe-Noire, Rep. of Congo
Silviculture and Agro forestry Coordinator 1988 – 1991
Ministère des Eaux et Forêts Brazzaville, Rep. of Congo
Internship January – July 1988
Unite d'Afforestation Industrielle du Congo Pointe-Noire, Rep. of Congo

PROFESSIONAL AFFILIATIONS:
- Society of American Foresters
- US – International Association for Landscape Ecology

Name: Georges Ferdinand Backoulou Date of Degree: December, 2008

Institution: Oklahoma State University Location: Stillwater, Oklahoma

Title of Study: USING MULTI-SPECTRAL IMAGERY TO DETECT AND MAP STRESS INDUCED BY RUSSIAN WHEAT APHID

Pages in Study: 113 Candidate for the Degree of Doctor of Philosophy

Major Field: Environmental Science

Scope and Method of Study: The rationale of this study was to assess the stress in wheat field induced by the Russian wheat aphid using multispectral imagery. The study was conducted to (a) determine the relationship between RWA and edaphic and topographic factors; (b) identify and quantify the spatial pattern of RWA infestation within wheat fields; (c) differentiate the stress induced by RWA from other stress causing factors. Data used for the analysis included RWA population density from the wheat field in, Texas, Colorado, Wyoming, and Nebraska, Digital Elevation Model from the Unites States Geological Survey (USGS), soil data from the Soil Survey Geographic database (SSURGO), and multispectral imagery acquired in the panhandle of Oklahoma.

Findings and Conclusions: The study revealed that the population density of the Russian wheat aphid was related to topographic and edaphic factors. Slope and sand were predictor variables that were positively related to the density of RWA at the field level. The study has also demonstrated that stress induced by the RWA has a specific spatial pattern that can be distinguished from other stress causing factors using a combination of landscape metrics and topographic and edaphic characteristics of wheat fields. Further field-based studies using multispectral imagery and spatial pattern analysis are suggested. The suggestions require acquiring biweekly multispectral imagery and collecting RWA, topographic and edaphic data at the sampling points during the phonological growth development of wheat plants. This is an approach that may pretend to have great potential for site specific technique for the integrated pest management

ADVISER'S APPROVAL: Dr. Norman Elliott